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Abstract

The utilisation of terrestrial ecosystems to satisfy the basic needs of humankind has profound impacts on the Earth System and led to the development of distinctive, human-dominated land systems. These land systems are substantially complex as they evolved from a multitude of land-change pathways driven by a variety of political, socio-economic, and environmental conditions. Current calls for a more sustainable future land-use require a sound understanding of this complexity, which should be integrative and extend existing approaches that mainly focus on land conversions and sectoral analyses. The main goal of this thesis is to better understand the spatio-temporal patterns and the determinants of land-system change in Europe between 1990 and 2010, especially with regard to land-use intensity. Europe serves as an interesting study region as it recently experienced a period of marked land-use change, and since its large environmental, political, and socio-economic heterogeneity resulted in a diversity of land systems and land-change pathways. Land-system changes in Europe were examined by (i) mapping patterns and changes in forestry and agricultural intensity and identifying the most influential spatial determinants related to these changes, and (ii) mapping and characterising archetypical patterns and trajectories of land systems considering both land-use extent and intensity indicators. Results revealed a distinct east-west divide in Europe's land-system patterns and change trajectories, with intensively used and intensifying regions particularly located in Western Europe. However, Europe was mainly characterised by relatively stable land-systems patterns with (de-) intensification trends being only of minor importance. Land-use intensity levels and changes were strongly related to site conditions, especially with regard to soil and climate, as well as to country-specific characteristics representing national legislations, policies, and traditions. By fostering the understanding of land-system change, this thesis has the potential to contribute to scientific and policy-related actions that address current efforts to guide future land systems in Europe to a more sustainable use.

Zusammenfassung

Die Nutzung von terrestrischen Ökosystemen zur Befriedigung der Grundbedürfnisse der Menschheit hat tiefgreifende Auswirkungen auf das Erdsystem und führte zur Ausprägung von charakteristischen, anthropogen dominierten Landsystemen. Diese Landsysteme sind von hoher Komplexität, da sie aus einer Vielzahl von politisch, sozioökonomisch und umweltbedingt angetriebenen Landnutzungsveränderungen hervorgegangen sind. Aktuelle Forderungen nach einer nachhaltigen zukünftigen Gestaltung der Landnutzung erfordern jedoch ein fundiertes und integratives Verständnis dieser Komplexität, welches bestehende, auf Landkonversionen und sektoralen Analysen beruhende Ansätze erweitert. Das Hauptziel dieser Arbeit ist es daher, unter besonderer Berücksichtigung der Landnutzungsintensität, ein besseres Verständnis der raum-zeitlichen Muster und der Determinanten des Landsystemwandels in Europa zwischen 1990 und 2010 zu erlangen. Europa ist ein interessantes Studiengebiet, da es jüngst starke Landnutzungsveränderungen erlebte und seine große ökologische, politische und sozioökonomische Heterogenität zu einer Vielfalt von Landsystemen und Landsystemveränderungen führte. Der Landsystemwandel in Europa wurde durch (i) die Kartierung von Intensitätsmustern und deren Veränderungen in Forst- und Agrarsystemen sowie der Ermittlung der dafür einflussreichsten räumlichen Determinanten und (ii) die Kartierung und Charakterisierung archetypischer Muster und Entwicklungsverläufe von Landsystemen mit Hilfe von flächen- und intensitätsbezogenen Landnutzungsindikatoren untersucht. Die Ergebnisse dieser Arbeit zeigten einen deutlichen Ost-West-Unterschied in Landsystemmustern und -veränderungen in Europa, mit intensiv genutzten und intensivierenden Regionen vor allem in Westeuropa. Dennoch waren (De-)Intensivierungstrends insgesamt nur von untergeordneter Bedeutung und Europa wurde vor allem durch relativ stabile Landsystemmuster gekennzeichnet. Die Landnutzungsintensität und deren Veränderungen waren stark an vorherrschende Standortbedingungen gebunden, vor allem an edaphische, klimatische, und länderspezifische Besonderheiten wie Rechtsvorschriften, Richtlinien und Landnutzungstraditionen. Diese Arbeit hat durch die Förderung des Verständnisses des Landsystemwandels in Europa das Potenzial, zur Entwicklung wissenschaftlicher und politikbezogener Maßnahmen beizutragen und somit die aktuellen Bemühungen zur Erreichung einer nachhaltigeren Landnutzung in Europa zu unterstützen.

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Chapter I: Introduction

1 Scientific background

1.1 Global environmental change and land use

Human life on Earth crucially depends on the functioning of ecosystems and the availability of services they provide. Since the beginning of human civilisation, societies utilised these services to satisfy their demand for food, fresh water, timber, fibre, and fuel and to safeguard human well-being (Ellis et al. 2013). By doing so, human activities influenced and in some cases irreversibly altered ecosystems and their functionality (Steffen et al. 2007), with an increasing spatial extent and magnitude of impact over time (Ellis et al. 2010, Ellis and Ramankutty 2008, Sanderson et al. 2002). Especially within the last decades, humankind affected ecosystems more rapidly and profoundly than ever before in human history (Steffen et al. 2015a, MA 2005b), which may herald the emergence of a new era: the Anthropocene (Crutzen 2002, Steffen et al. 2004). Human activities on Earth are the dominant cause for the observed global environmental change (MA 2005b, Vitousek 1994) by degrading the majority of ecosystem services (MA 2005b), increasing greenhouse gases emissions responsible for the warming of the atmosphere and oceans (IPCC 2014), and causing declines in terrestrial and aquatic biodiversity (Dirzo et al. 2014, McCauley et al. 2015). As the utilisation of ecosystem services relies on finite resources, their exploitation puts enormous pressure on natural ecosystems (Steen-Olsen et al. 2012, Weinzettel et al. 2013). These anthropogenic pressures on the Earth System have led to reaching and even transgressing planetary boundaries within which humanity can operate safely (Steffen et al. 2015b, Rockström et al. 2009). Facing humanity's dilemma of depending on natural ecosystems and concurrently degrading them, sound knowledge on understanding human-environment systems is urgently needed to ensure the sustainment of functioning ecosystems for future generations and consequently human well-being (Haberl et al. 2006, Turner II et al. 2003).

Land systems are integral parts of human-environment systems as they represent the interface between most human activities and the natural environment, thus offering great potential to investigate humanity's role in the Earth System. The way how humans utilise the Earth's terrestrial surface and its biotic and abiotic components is defined as *land use* (Lambin et al. 2006). Anthropogenic activities such as agriculture, forestry, mining, transport, or housing influence and modify the state and function of land by either transforming natural ecosystems (such as forests, savannahs, or grasslands) into human-dominated systems (such as croplands, pastures, or plantations) or by managing land-use systems with different degrees of intensity (such as higher/lower degree of mechanisation, fertiliser applications, or logging rates) (SOER 2010). This process is defined as *land-use change*, from which humanity has strongly benefited because it allowed for the provisioning of essential food, feed, fibre, and bioenergy (Foley et al. 2005). Nevertheless, land use and land-use change also entailed considerable environmental impacts that reach back millennia (Ellis et al. 2013). Especially over the last 300 years, land change increased substantially in terms of its spatial extent and intensity (Ellis et al. 2013), resulting in manifold modifications of the Earth System such as increased greenhouse gas emissions (Burney et al. 2010), amplified climate change (Kalnay and Cai 2003, Luyssaert et al. 2014), and alterations of the global nitrogen and phosphorus cycles (Galloway et al. 2008, Cordell et al. 2009). Furthermore, land-use change led to the loss and degradation of ecosystems and their services (Kareiva et al. 2007), for example the degradation of soil and water quality (Foley et al. 2005) or declines in biodiversity (Newbold et al. 2015, Pereira et al. 2010). In concert, these modifications and their consequences made land use the most visible indicator of the human footprint on Earth (UNDESA 2012), which negatively affected ecosystem service availability, human well-being, and the long-term sustainability of human societies (SOER 2010, Foley et al. 2005, DeFries et al. 2004).

In light of the expected continuation of population growth to over 9 billion people (Gerland et al. 2014), presumed shifts in consumption habits to more affluent diets with higher consumption of meat and processed food (Reisch et al. 2013, Kearney 2010), and the increasing role of bioenergy (Beringer et al. 2011), the global demand for land-based products is likely to increase throughout the 21st century (Foley et al. 2011, Godfray et al. 2010, Kastner et al. 2012, Tilman et al. 2002, FAO 2014). Globally, food demand from agriculture is expected to approximately double (World Bank 2007) while the wood demand from forests and plantations is projected to triple (WWF 2012) by 2050. Considering the enormous past and current impacts of land use and land-use change (Butchart et al. 2010, DeFries et al. 2010, Tilman et al. 2009, Foley et al. 2005), the question how this demand can be satisfied in a sustainable and socially equitable way is a central challenge humanity faces in the 21st century (Foley et al. 2011, Tilman et al. 2011).

Main levers for shifting land-based production systems to sustainable use are arguably on the demand side, such as changes in consumption habits, improvements in food access and distribution, as well as reductions in food wastage (Tilman and Clark 2014, Garnett et al. 2013). These changes might not appear in the short run due to time lags, policy failures, or the inert behaviour of consumers. Hence, overall increases in agricultural and forestry production are essential for meeting the growing demand for these products and to facilitate food security from the supply side (Garnett et al. 2013, Benton et al. 2011, Tilman et al. 2011), to which both, agricultural and forest systems, contribute either directly (e.g., crops, meat, wild foods) or indirectly (e.g., by ensuring dietary diversity, micronutrient intake, or productive food systems) (van Zanten et al. 2014, Sunderland et al. 2013). Though food security will not automatically be improved by mere production increases (Tscharntke et al. 2012), such increases will have an important part to play in meeting the demands of a growing world population (Godfray et al. 2010).

Generally, two modes exist to achieve production increases: the *expansion* of land-based production systems on the one hand and the *intensification* of existing production systems on the other (Tilman et al. 2011). While expansion refers to converting land from one category into another (e.g., the change from natural forests to agricultural areas due to deforestation), intensification occurs within the same land-use category without changing its general characteristics but with increasing inputs to or outputs from a unit of land per time period (Lambin et al. 2003). Both modes of land-use change have negatively affected the Earth System and transformed the natural environment (Foley et al. 2005), to the point that currently the majority of fertile land is under human management and three quarters of the global ice-free terrestrial surface experienced human-induced alterations (Ellis and Ramankutty 2008). Thus, available fertile land is increasingly becoming scarce (Lambin and Meyfroidt 2011) and further expansion of land use into remaining wildlands will incur high environmental and socio-economic costs in affected regions (Garnett et al. 2013). This leads to a rising competition for land and land-based products (Lambin and Meyfroidt 2011, Smith et al. 2010), as actors with different land-use interests (e.g., agro-businesses, conservationists, small-holders) struggle for the utilisation of the remaining fertile lands. Considering this, most of the anticipated future increments in land-based production will consequently have to rely on increasing the output per land unit already in use rather than on the expansion of land use (Foley et al. 2011, Tilman et al. 2011, Bruinsma 2003).

1.2 The role of land-use intensity in land-based production systems

Land-use intensity is a complex, multidimensional term that plays out differently across space and time. It can be measured in terms of input metrics (e.g., land, labour, use of fertilisers, pesticides, and machinery), output metrics (e.g., yields, caloric/protein/monetary value), and system metrics (e.g., yield gaps, human appropriated net primary production)

(Erb et al. 2013a, Kuemmerle et al. 2013). In the 18^{th} century, Malthus (1798) abstracted from the concept of land-use intensity when he assumed that agricultural production increases only linearly with land and labour inputs, thereby limiting the exponentially increasing population size. This view was challenged by Boserup (1965), who characterised agricultural intensification as a response to population growth and related demand increases. Further, she reversed Malthusian-based views that the state of technology (i.e., agricultural practices and innovations) determines the levels of cropping intensity by arguing that much of technological innovations are endogenously driven by pressures on production systems (Turner and Shajaat Ali 1996).

In sensu Boserup, Ellis et al. (2013) defined land-use intensification as an “adaptive response of human populations to demographic, social, and economic pressures leading to the adoption of increasingly productive land-use systems”. The general trend towards increasing land-system productivity with increasing population pressure is depicted as a complex succession of regime shifts in land systems. The first stage is characterised by Boserupian intensification with advances in technology that allow for faster and larger increases in productivity than in population size. This stage is followed by the involution of production where only net input increases allow for production increases (Geertz 1963). The last stage is characterised by Malthusian crisis where exhausted production capacities result in faster population growth than productivity increase. Technological innovations (e.g., the Haber-Bosch process in the early 20th century) and demographic or societal demands for surplus production or reduced labour inputs then trigger a regime shift to a new level of productivity (Ellis et al. 2013).

Land-use intensification played an important role for meeting the demand for land-based production. Whereas production increased mainly because of the spatial expansion of land-use systems over long timescales, land-use intensification first spurred in Europe in the mid-19^{th} century as the “Second Industrial Revolution” and associated technological advances such as new machinery and fertilisers allowed for improved land management (Jepsen et al. 2015). For forests, one of the most important factors of intensified management was the substantial replacement of deciduous vegetation by coniferous tree species in these times, shifting multipurpose to single-use forests that were predominantly used for intensive timber production (McGrath et al. 2015, Meyfroidt and Lambin 2011). Agricultural intensification accelerated especially since the mid-20^{th} century when substantial production increases were now mainly achieved along intensification gradients (Byerlee et al. 2014, Bruinsma 2003, Matson et al. 1997). This process that came to be known as the Green Revolution substantially improved land-use efficiency (Borlaug 2007, Krausmann et al. 2013). Technological developments, the additional input of fertilisers, pesticides, and labour, and the increased mechanisation and irrigation allowed for the more than two-fold increase in global crop production at largely stable cropland extent (Rounsevell et al. 2012, Borlaug 2007).

Despite the advantages in human well-being due to past land-use intensification, many of the applied techniques for enhancing land-based production also entailed substantial and far-reaching detrimental ecological and social effects that may have undermined the long-term functionality of ecosystems (Erb et al. 2013a, Foley et al. 2005, Matson et al. 1997). In agriculture, intensive management is often characterised by large-scale, monoculture plots and high rates of fertiliser (especially nitrogen and phosphorus), pesticide, and water consumption. This had manifold implications such as the increased risk of soil erosion due to hedgerow removals and drainage systems (Foucher et al. 2014), soil degradation due to the loss of soil organic matter and disturbed soil biota communities (Postma-Blaauw et al. 2010), and soil salinisation and a decline in water quality and availability due to irrigation practices (Foresight 2011). Intensive farming practices also led to the pollution and eutrophication of ground and surface waters caused by leaching, run-off, drainage, and aerial drift of chemical inputs (Tilman et al. 2011) and to a substantial decline in biodiversity (WWF 2014, Tscharntke et al. 2005). Furthermore, rising fertiliser application and livestock densities increased greenhouse gas emissions from agriculture, thereby contributing to the global warming (Tilman et al. 2011, Robertson et al. 2000). Intensifying forest management had negative repercussions on forest ecosystem services as intensively managed forests, often monoculture stands, reduce biomass production, carbon storage, available dead wood, and biodiversity (Gamfeldt et al. 2013, Paillet et al. 2010, Jandl et al. 2007). Furthermore, intensively managing medium aged and mature stands impaired forest structure by decreasing the share of old forests and mean forest age (Vilén et al. 2012).

Considering the substantial environmental impacts of past and current land-use intensification, growing concerns about the long-term functionality of ecosystems, and the challenge to feed a growing world population, there is an urgent need for sustainably increasing future land-based production. The issue of how to increase current and future land-based production in a sustainable way has been addressed in different ways under the overarching term *sustainable intensification*, which aims at increasing land-based production while minimising the negative environmental impacts and further expansion of production systems (Godfray and Garnett 2014, Pretty and Bharucha 2014).

1.3 Sustainable intensification

Defining sustainable intensification is not a simple task when considering the economic, social, and environmental dimensions of sustainability as well as the multitude of spatial and temporal scales at which such definitions can operate (Smith 2013). For the agricultural sector, Smith (2013) borrows from the definition of sustainability by Brundtland et al. (1987) and defines sustainable intensification as “delivering more safe, nutritious food per unit of input resource, whilst allowing the current generation to meet its needs without compromising the ability of future generations to meet their own needs”. In the forestry sector, sustainable intensification is interpreted within the framework of sustainable forest management (FAO 2014). This framework aims at stewarding and using “forests and forest lands in a way and at a rate that maintains their biodiversity, productivity, regeneration capacity, vitality and their potential to fulfil, now and in the future, relevant ecological, economic and social functions, at local, national and global levels, and that does not cause damage to other ecosystems” (Forest Europe et al. 2011).

A theoretical concept that addresses the aims of sustainable intensification on a landscape-planning level is a landscape optimisation approach via zoning, which is also described as *land-sparing*. Land sparing seeks to safeguard the remaining areas that are largely untouched by human land-use activities by focussing on the maximisation of land-based production on already used, fertile lands. In doing so, the pressure to convert land for anthropogenic purposes is anticipated to decrease, a hypothesis first formulated by Borlaug for the agricultural sector (c.f., Angelsen and Kaimowitz 2001, Borlaug 2007). This would spare these lands for other uses, which may be beneficial for the protection of forests, the sequestration of carbon, or the conservation of biodiversity (Erb et al. 2013a). Land-use intensification can have great potential for such land-sparing effects (Phalan et al. 2011, Green et al. 2005), exemplified by the livestock (Steinfeld et al. 2006), cropland (Macedo et al. 2012, Foley et al. 2011), and forestry (Brockerhoff et al. 2008, Bowyer 2001) sectors.

However, land-use intensification in a land-sparing fashion may actually fail to increase the amount of land that will be spared for nature (Tscharntke et al. 2012, Perfecto and Vandermeer 2010), for example due to rebound effects (Lambin and Meyfroidt 2011). There is evidence that efficiency improvements in the usage of natural resources (e.g., higher yields) lead to higher profitability (e.g., financial returns on land), which acts as an incentive for further consumption increases (Byerlee et al. 2014, Angelsen 2010, York 2006). This paradox was already described by Jevons (1866) in the 19th century and examples in land-use science include the soybean production in Brazil and Indonesia that led to substantial deforestation as high market prices for soybeans and increased yields though agricultural intensification improved production profitability (Nepstad and Stickler 2008, Angelsen and Kaimowitz 2001).

In contrast to land sparing, *land sharing* favours agro-ecological systems that are characterised by combining land-based production with wildlife-friendly farming techniques via low management intensity with regard to capital and chemical inputs but high intensity of labour and land requirements (Clough et al. 2011, Fischer et al. 2008). However, the discourse on whether land sparing or land sharing will result in better outcomes in terms of land-based production and ecosystem protection is largely based on an “either-or” dichotomy (Kremen 2015). Considering that benefits of land sparing or land sharing are strongly scale- and place-dependent (Grau et al. 2013), both strategies should not be treated as mutually exclusive but rather be used to create synergies between protected regions and favourable surrounding matrices while satisfying human demands for land-based production (Fischer et al. 2014, Kremen 2015).

Targeting sustainable intensification from a land-management perspective, one prominent proposition is to secure high yields on existing croplands where yields are suboptimal (Tilman et al. 2011). By closing yield gaps, production increases could be realised without the negative effects of further land conversions into agricultural areas. This could be realised by adapting new technologies, using high-yielding crop varieties, or re-organising the currently imbalanced distribution and availability of external inputs such as fertilisers or irrigation water (Tilman et al. 2011, Mueller et al. 2012, Foley et al. 2011). Other yield-improving measures embrace improved fertiliser and soil management, precision farming, better nutrient recycling, and the consideration of bioclimatic conditions for crop growth (Smith 2013). For example, improved nitrogen use efficiency matches nitrogen input with seasonal and quantitative crop needs and thus allows for maintaining yields while reducing nitrogen losses to the environment (Lassaletta et al. 2014). Possibilities to achieve sustainable intensification goals include the reduction of harvest-related soil and vegetation damage, the maintenance of stand genetic diversity by selective logging, or the increase of timber removals in regions where wood production is well below the natural biomass increment (Levers et al. 2014, Duinker et al. 1998).

Despite providing opportunities for production increases at lower environmental costs, the concept of sustainable intensification also entails major drawbacks. First, by mainly focussing on production outputs and environmental impacts, the concept of sustainable intensification as a strategy to ascertain food security misses to account for shortages in food distribution and availability, crop losses or food wastage, and the fact that food crops are not only used for human consumption (Weinzettel et al. 2013, Loos et al. 2014). Second, sustainable intensification in its current form does not consider the socio-economic dimensions of sustainability, intra- and intergenerational justice, and the improvement of human well-being from local to global scales (Brundtland et al. 1987, Loos et al. 2014). Third, many means of sustainable intensification bear their own disadvantages. For example, the additional inputs that are required to intensify existing production systems in order to reduce yield gaps, such as fossil energy, nitrogen, phosphorus, or fresh water, are themselves limited and their (amplified) use may lead to negative ecosystem impacts (Weinzettel et al. 2013, Loos et al. 2014, Fischer et al. 2011).

However, considering the growing demand for food, feed, fibre, and bioenergy as well as the large environmental trade-offs of current production practices, a way to increase land-based production sustainably is urgently needed. Maintaining the status quo of current land use and land-use intensity is clearly no role model for the future, notwithstanding the fact that past land-use intensification saved between 18 and 27 million hectares land from being brought to agricultural production (Stevenson et al. 2013). Future land-use has to address the current unsustainable land-use practices in all of its dimensions, and build resilience against future threats such as global warming (Schmidhuber and Tubiello 2007) to satisfy the needs of a growing world population and to safeguard human well-being.

2 Motivation and research gaps

As outlined above, land-use strategies have to be modified to concurrently meet future demands for land-based products and to achieve a more sustainable way of utilising ecosystems. For improving land-use strategies towards these goals, deeper knowledge on and a better understanding of patterns and determinants of land-system change is needed. Existing studies that investigate land-system changes focus majorly on land-use conversion processes (Erb 2012), regardless of the growing recognition of the importance of land-use intensity for understanding land systems (Luyssaert et al. 2014, Erb et al. 2013a). Despite their major importance for past, current, and future provision of land-based production to human societies and their substantial environmental impacts, the analysis of land-use intensity and land-use intensification have thus been mostly neglected by the scientific community so far (Kuemmerle et al. 2013). This is largely due to a lack of data with an adequate spatial and temporal resolution, the multidimensionality of land-use intensity, and varying intensity indicator definitions, which all impede the assessment of land-use intensity (Kuemmerle et al. 2013).

However, addressing these shortcomings is urgently needed if land systems and their utilisation are supposed to transfer to a more sustainable state. Assessing where future production could be increased sustainably and understanding the social, economic, and environmental trade-offs of land-use changes requires sound and consistent knowledge about the *spatial patterns* and *determinants* of land-use intensification pathways as well as *archetypical patterns and change trajectories* of land systems, especially at broad geographic scales and with high spatial detail (Verburg et al. 2009, Erb 2012). This knowledge is currently strongly limited, which is particularly unfortunate considering the importance of regional and continental scales for policy making and for mitigating global environmental change impacts (Wu 2013).

2.1 Europe as an example to study land-system change

Europe provides an interesting case to study land-system changes due to several reasons. First, Europe experienced a period of marked land-use change historically and recently, including both changes in the extent and intensity of agriculture and forestry, that led to a large diversity of land systems and multifaceted land-change pathways (Jepsen et al. 2015, Rounsevell et al. 2012, Vos and Meekes 1999). Europe’s land system is dominated by anthropogenic landscapes with agricultural (42%) and forest areas (35%) occupying the largest share of its territory, the latter consisting majorly of semi-natural stands and plantations (SOER 2010). Europe’s land system was characterised by land conversions for a long time before land use predominantly changed along intensification gradients in the second half of the 20th century (Rounsevell et al. 2012). Europe’s agricultural systems experienced a substantial intensification in the 1960’s to 1980’s after a period of expansion, mainly on the expense of forests and grasslands (Kaplan et al. 2012). Currently, Europe harbours some of the most intensively managed agricultural areas worldwide (Haberl et al. 2007, Mueller et al. 2012). Concurrently, the spatial extent of agriculture declined in marginal areas that offered less suitable conditions for production (MacDonald et al. 2000, Navarro and Pereira 2012), which resulted in the widespread loss of traditional agricultural landscapes (Fischer et al. 2012) and an overall increase of Europe’s forest cover since the 1950’s (Gold et al. 2006, Fuchs et al. 2013). Together with afforestation and nature protection practices, re-growing woody vegetation on former agricultural areas contributes to the forest transition taking place in Europe after the Industrial Revolution (Kaplan et al. 2012, Rudel et al. 2005), counterbalancing the previous, substantial deforestation in order to satisfy the demand for agricultural land, timber products, and energy. Furthermore, the structure of Europe's forest was modified due to changes in forest management, nitrogen deposition, and climate change (Erb et al. 2013b, Fernández-Martínez et al. 2014, Pretzsch et al. 2014). The European Union considerably expanded its conservation network (Jones-Walters and Čivić 2013) and emphasised landscape multifunctionality by considering environmental costs of land-use intensification, for example through policies such as agri-environmental and set-aside schemes (Whittingham 2011).

Second, Europe experienced drastic institutional changes between World War II and the breakdown of the Soviet Union in 1989 (Kuemmerle et al. 2006). In this period, Europe's economy was characterised by a market-driven economy in Western and a central planning economy in Eastern Europe, which had marked influences on the management of the respective land systems (Prishchepov et al. 2012). The breakdown of the Soviet Union with the resulting change from a planning to market economy and the subsequent eastward expansion of the EU triggered widespread land-use change (Munteanu et al. 2014, Kuemmerle 2008), both in agriculture (Griffiths et al. 2013b, Müller et al. 2009) and forestry (Griffiths et al. 2013a, Ellis et al. 2010, Kuemmerle et al. 2007) Furthermore, legacy effects of the differently managed land systems are still visible today, resulting in a marked east-west divide, especially for land-management intensity. For example, land-use intensification began later and at slower rates in Eastern Europe compared to the Western countries, resulting in generally higher land-use intensity in Western Europe (Jepsen et al. 2015).

Third, Europe's utilisation of terrestrial surface for land-based production is one of the highest on the globe and the expansion of production systems into remaining (semi-) natural areas are strongly constrained (Haberl et al. 2007). Despite this, Europe revealed considerable increases in per capita food supply with decreasing per capita cropland requirements. This can be partly explained by improved land-use efficiency (i.e., how efficient the human appropriation of net primary production is converted to land-based products, Plutzar et al. 2015) and related land-use intensification but also by international trade (Kastner et al. 2015), which allowed for relieving pressure on Europe's production systems and ecosystems by importing goods from locations outside of the European boundaries. More than half of the land footprint associated with products consumed in the EU is displaced to the locations of production (EEA 2014, Wackernagel et al. 2002), equalling approximately 16% of the total global land footprint by only covering 7% of the Earth’s terrestrial surface (Weinzettel et al. 2013, Steen-Olsen et al. 2012).

Fourth, changes in policy instruments (e.g., the Common Agricultural Policy or EU Forest Strategy) markedly influenced land systems in large parts of Europe (Donald et al. 2002, Forest Europe et al. 2011). These land systems are managed and stewarded by policies acting on different spatial scales and can be grouped into three general categories (SOER 2010): (i) integrated programmes for land-use planning and management, (ii) targeted policy instruments for specific locations or land-use sectors, and (iii) sectoral policies focussing on economic drivers. An important example for category (i) is the European Spatial Development Perspective (EC 1999b). However legally non-binding, this framework aimed at coordinating the manifold regional policy impacts in Europe and advocated the long-term sustainability of Europe's land use. It aimed at ensuring economic cohesion, the conservation and management of natural resources and cultural heritage, and a more balanced competitiveness of the European territory (EC 1999b). Important examples for category (ii) are the Natura 2000 directive or the Pan-European Ecological Network (PEEN) that try to balance biodiversity conservation and the human use of natural resources (SOER 2010).

The Common Agricultural Policy (CAP) is arguably the most important policy for category (iii). Implemented as the “Treaty of Rome” in 1957, it initially aimed at increasing agricultural productivity, ensuring a fair living standard for farmers and reasonable prices for consumers, stabilising markets, and assuring sufficient food supply (Swinnen 2014). CAP policies (price supports, import tariffs, and export subsidies) triggered changes in agricultural management and were a major incentive for agricultural intensification that turned the European Union from a net importer to a net exporter of food (van Zanten et al. 2014, Swinnen 2014). CAP policies also had marked impacts on European landscapes (Lefebvre et al. 2012). They lead to the scale enlargement of farms and the abandonment of marginal agricultural areas (van Zanten et al. 2014) that generally resulted in landscape homogenisation (Jongman 2002) and the polarisation of agricultural areas (Plieninger et al. 2014, Weissteiner et al. 2011). Since the 1990’s, the CAP underwent several reforms and was transformed from a production subsidy to an income subsidy system promoting cost-efficient agriculture (Lowe et al. 2002, van Zanten et al. 2014). As a response to the substantial environmental impacts related to the agricultural intensification triggered by CAP policies (Donald et al. 2002, Stoate et al. 2001), agri-environment schemes were introduced and single farm payments were subject to the cross-compliance of farmers to environmental standards. EU-wide policies for the forestry sector include the EU Forest Strategy (EC 1999a) that aimed at implementing sustainable forest management principles and the succeeding EU Forest Action Plan (EC 2006a) with the target to maintain and enhance biodiversity, carbon sequestration, and the integrity, health, and resilience of forest ecosystems (SOER 2010).

The described environmental, political, socio-economic, and institutional changes markedly influenced Europe's land system. How these changes relate to land-system patterns and trajectories remains unclear, especially with regard to the influence of land-use intensity changes. While general trends in land conversions can be identified based on results of the EU initiative "Coordination of Information on the Environment" (CORINE), knowledge on the rates, spatial patterns, and determinants of intensification pathways in Europe are currently strongly limited. Hence, there is an urgent need to gain a better understanding of land-system changes in Europe, thereby explicitly focussing and incorporating information on land-use intensity. This would allow for informing decision makers, especially the European Union as the supranational body steering land-use, to design targeted and regionalised policies for reaching a more sustainable future land use in Europe.

2.2 Patterns and determinants of land-use intensity change

Spatial patterns in land use (intensity) and changes therein are results of decisions by land-use actors, which are influenced by multiple factors of ecological, societal, and economic origin. These factors can be broadly subdivided into two categories: (i) proximate causes that are bound to local-scale land-use decisions and (ii) underlying causes that often play out at regional to global scales (Geist et al. 2006). Underlying causes, or drivers, of land-use change operate at different spatial and temporal scales (Lambin and Geist 2006), ranging from local (e.g., topography, soil quality) over regional (e.g., climate) to global scales (e.g., macro-economy) and from shorter (e.g., market prices) to longer (e.g., policies, demographic change) time horizons. Changes in underlying drivers have repercussions on local-scale proximate causes that lead to changes in land-use activities and consequently to land-use change (Geist et al. 2006). As broad-scale, underlying drivers of land-use change are difficult to assess due to their often gradual temporal changes and low spatial variability, spatial determinants are commonly used as indirect proxies of underlying drivers in order to investigate their influence of observed patterns of land-use change. Several shortcomings exist that leave a major research gap for analyses that explicitly address subnational but broad-scale patterns and spatial determinants of forest management intensity and agricultural intensity (Erb et al. 2013a, Kuemmerle et al. 2013).

In forestry, spatial patterns and determinants of forest management intensity are highly unclear. Existing studies that addressed forest management intensity majorly focussed either on national scale data (Kuusela 1994, Forest Europe et al. 2011), thereby omitting subnational heterogeneity, or on small study areas (cf. Schall and Ammer 2013), which are difficult to generalise from. Further, information on decisions how intensively forest owners manage their stands are also limited to local case studies of mostly non-industrial, privately owned forests (cf. Beach et al. 2005). Consequently, there is a research gap to investigate the spatial patterns and determinants of forest management intensity at broad geographic scales using subnational data to provide spatially coherent and detailed information.

Current assessments of forest management intensity have two main limitations. First, they rely on wood production volumes only, which can be misleading as the same volume of timber extraction can result in regionally different intensity levels considering ecosystem productivity. Second, data on wood production itself is only available at administrative unit level, which is likely too coarse for designing and implementing spatially targeted policies aiming at sustainable forest use in terms of production. Hence, there is a need for a measure that allows the comparison of forest harvesting management intensity across large regions and ecosystem gradients. Further, spatially explicit information on wood production are required (Maes et al. 2012), which are commonly achieved by disaggregating wood production statistics based on forest cover (i.e., higher forest cover relates to higher timber harvesting). Yet, this simplistic approach can result in substantial errors (Eigenbrod et al. 2010), as wood production patterns may be different across forest landscapes. Hence, a research gap exists to consider other determinants, such as accessibility or tree species compositions, for disaggregating wood production patterns to the pixel level.

In agriculture, substantial progress has been made recently in mapping broad-scale spatial patterns of agricultural intensity (e.g., Fritz et al. 2015, Robinson et al. 2014, van Asselen and Verburg 2012, Temme and Verburg 2011, Neumann et al. 2010). However, apart from the identifying drivers of agricultural land-use change based on case-study evidence (van Vliet et al. 2015a) only few studies have quantitatively analysed patterns and determinants of agricultural intensity change at broad geographic scales with subnational resolution.

Furthermore, these studies were often restricted in space (e.g., only for specific countries or the EU15) or time (e.g., to a single target year) and commonly focus on a single intensity indicator (often yields only) and agricultural sector (i.e., cropland or grassland). Hence, there is a need to investigate subnational changes in agricultural intensity patterns on pan-European scale while considering the multidimensionality of agricultural intensity.

Regression techniques proved to be powerful tools for the identification of important factors related to land-use patterns and changes therein as well as to disaggregate national- or regional-level data to the pixel level (so-called dasymetric mapping). Therefore, data models such as logistic or linear regressions are traditionally used. These models rely on a-priori assumptions on the distribution of the data and on the, often linear, relationship between target and predictors. This may result in difficulties and inaccuracies to accurately and robustly describe land-use patterns or changes considering the complexity of human-environment systems often characterised by nonlinearities (Müller et al. 2013). Algorithmic models, which belong to machine learning techniques, alleviate these limitations to some extent by assuming that the process behind the observed phenomenon is complex and unknown. These models are, in comparison to data models, distribution-free and these fewer requirements on the data structure make them well-suited to investigate the complex and often non-linear characteristics of land-use patterns and changes (Breiman 2001b, Elith et al. 2008). Specifically, Boosted Regression Trees provide a wide range of desirable features for such kind of analysis, such as high predictive accuracy, handling of non-linearity and interaction effects, good interpretability, and robustness against overfitting, missing data, and predictor collinearity (Dormann et al. 2013, Hastie et al. 2011, Elith et al. 2008, Friedman 2001). Despite their great potential to provide improved knowledge on determinants of land-use patterns and changes, only few studies in land-system science have so far used such models.

2.3 Archetypes of land-system patterns and change trajectories

Land systems and changes therein are characterised by substantial complexity as the two modes of land-use change, land conversions and changing management intensity, result in manifold land-change pathways that are related to various influential factors. Considering land conversions and changes in land-use intensity in a consistent framework allows for better understanding the complexity in land systems, for holistically assessing land-system patterns and change trajectories, and for assessing impacts and trade-offs of land-system changes on biodiversity and ecosystem service supply. Similar to the *syndromes* approach

(Petschel-Held et al. 1999, Petschel-Held 2004), so-called *archetypes* distil land-system complexity into unique and regularly appearing sets of land-use patterns and changes, thereby explicitly accounting for the multidimensional aspects of land-use intensity (Václavík et al. 2013). In combination with proximate and underlying drivers of land-use change, this approach provides spatially explicit information on the most important characteristics of human–environment interactions. Despite calls for such integrative land-system analyses by jointly analysing information on area and intensity changes (Verburg et al. 2009), the majority of existing studies neglected important links between both modes of land change by focussing on individual land-change processes only. These interactions include possible feedback effects between land-use categories such as landscape polarisation (Plieninger et al. 2014, Stoate et al. 2009), rebound effects (Lambin and Meyfroidt 2011, Gasparri and le Polain de Waroux 2014), or telecouplings as spatially disparate linkages between area and intensity changes (Kastner et al. 2014). Most existing land-system characterisations dominantly focus solely on land cover and changes therein, thereby neglecting information on land-use intensity, or are restricted to a single point in time, thereby neglecting information on land change. Consequently, there is an urgent need for analyses that (i) jointly consider patterns and changes in land-use extent and intensity, (ii) include multiple land-use categories, and (iii) operate at spatial resolutions and extents relevant for more targeted, context specific, and regionalised policy-making.

Self-Organising Maps are well-suited to reduce the complexity of land-system patterns and changes therein and to consequently map archetypical patterns and trajectories of land-system change. This automated clustering technique is based on an unsupervised learning algorithm that maps high-dimensional input data based on their similarity in feature space to a low-dimensional array (Kohonen 2001). Self-Organising Maps are especially suited to deal with spatial data as they are typology preserving. Neighbourhood relations are maintained as proximate observations in input space are mapped to adjacent locations in output space (Kohonen 2001). Furthermore, Self-Organising Maps are less dependent on expert rules and threshold selection and are not restricted by the number of input features (Václavík et al. 2013), which is a preferable property considering the multitude of land-use (intensity) indicators for mapping archetypes of land-system patterns and change trajectories. So far, only few studies employed this powerful technique to address land-system related questions.

3 Conceptual framework

3.1 Research questions

The overarching goal of this thesis is to better understand recent spatial patterns of land-system change in Europe, majorly focussing on the period between 1990 and 2010, by (i) mapping patterns and changes in land-use intensity for land-based production systems (i.e., forests and agricultural areas), (ii) identifying their most influential spatial determinants, and (iii) mapping and characterising archetypical patterns and trajectories of land systems.

To reach this goal, this thesis is subdivided into two main parts: First, spatial patterns and determinants of land-use intensity and intensification trajectories in Europe were assessed. Second, the resulting information from part 1 were used to characterise similar patterns and change trajectories of land systems in Europe, so-called archetypes. Both parts foster knowledge on recent land-system changes in Europe, especially considering information on both, land cover and land-management intensity, and lead to the following research questions:

<u>Research Question I</u>: *What are the spatial patterns of recent land-use intensity changes in Europe and which spatial determinants are most influential for these?*

Better understanding land-system changes in Europe builds upon improved knowledge on patterns and determinants of land-use intensity and changes therein as this is largely neglected in current research. Solely assessing land-conversions bear the risk to overlook changes that occur within one land-use category and may change land-system properties. Especially considering Europe's large environmental, political, socio-economic, and historical heterogeneity, the multidimensionality of land-use intensity, and the manifold intensity indicators, different factors are likely to be influential for changes in land systems. Knowing where land-use intensity is high, where it changed, and which factors were influential for this allow for identifying trade-offs between land use and the environment and can inform policy makers to design regionalised, targeted measures towards a more sustainable land management.

Research Question II: *Where are similar patterns and change trajectories of land systems in Europe located and what are their characteristics?*

Changes of land cover and land-use intensity as the two modes of land change typically result in diverse patterns and trajectories of land-system change. Identifying regions with similar characteristics in terms of land-system patterns and change trajectories, so-called archetypes, allows for reducing this complexity. Further, the spatial association between land-system patterns and change trajectories facilitates the assessment whether a specific land-change process led to a specific land-system pattern or whether a specific land-system pattern evolved from one or from multiple land-change processes, thereby revealing possible path-dependencies. Moreover, evaluating the co-occurrence between archetypes and explanatory factors of land change allows for unravelling possible determinants that triggered respective patterns and changes. Answering this research question can ultimately serve useful to identify regions within which similar policy tools could be applied and to inform decision makers to develop context-specific land-management policies.

3.2 Approach and objectives

Addressing the goals of the two research questions is challenging, because consistent, broad-scale data on land-use intensity patterns and changes is scarce and available data are often only available with temporal or spatial restrictions (Kuemmerle et al. 2013). This thesis builds upon sub-national, multi-temporal data on land-use and land-use intensity patterns and changes in Europe. To answer *Research Question I*, this thesis relies on data at the administrative unit level, derived from official statistical databases to ensure spatial consistency and reliability. To answer *Research Question II*, spatially explicit data derived from land-use models and satellite imagery were used. The utilisation of these data sets facilitates a detailed characterisation and investigation of land-system change, in particular with regard to land-use intensity, at pan-European scale with the highest spatial and temporal resolution available during the time span of this thesis.

Specifically, forest harvesting statistics between 2000 and 2010 were collected on administrative-unit level from national reports, statistical yearbooks and databases, and by contacting national experts to assess forest harvesting intensity and disaggregate wood production in Europe. To investigate agricultural intensity in Europe, data on yields and fertiliser application between 1990 and 2007 were gathered on administrative-unit level from the Common Agricultural Policy Regionalised Impact (CAPRI) Modelling System database. For the identification of archetypical changes of land-system patterns and change trajectories, land-cover and land-use intensity patterns were obtained at a 1km^2 resolution for the years 1990 and 2006 from published, peer-reviewed studies and data sets. All environmental and socio-economic data, which were used to explain and characterise observed land-system patterns and changes therein, were obtained from publicly available or peer-reviewed data sources, ideally at 1km^2 spatial and annual temporal resolution.

In order to identify the most important spatial determinants of land-use intensity patterns and changes as well as to disaggregate data on administrative-unit level, this thesis relied on regression techniques, which are common tools for this purpose in land-system science. Specifically, Boosted Regression Trees were used to investigate spatial patterns of forest harvesting intensity in Europe and, in combination with Bayesian Model Averaging, to disaggregate wood production statistics to the pixel level. To assess the spatial determinants of changes in agricultural intensity patterns in Europe, random effects panel regressions were used. This technique represents the state-of-the-art for analysing longitudinal data on administrative-unit level as no algorithmic model exists that allows to handle such data. For mapping archetypical land-system patterns and changes, Self-Organising Maps were used as this automated cluster algorithm is especially suited for spatial clustering of high-dimensional data due to its topology-preserving properties. Figure I-1 provides a schematic overview of the approach employed in this thesis.

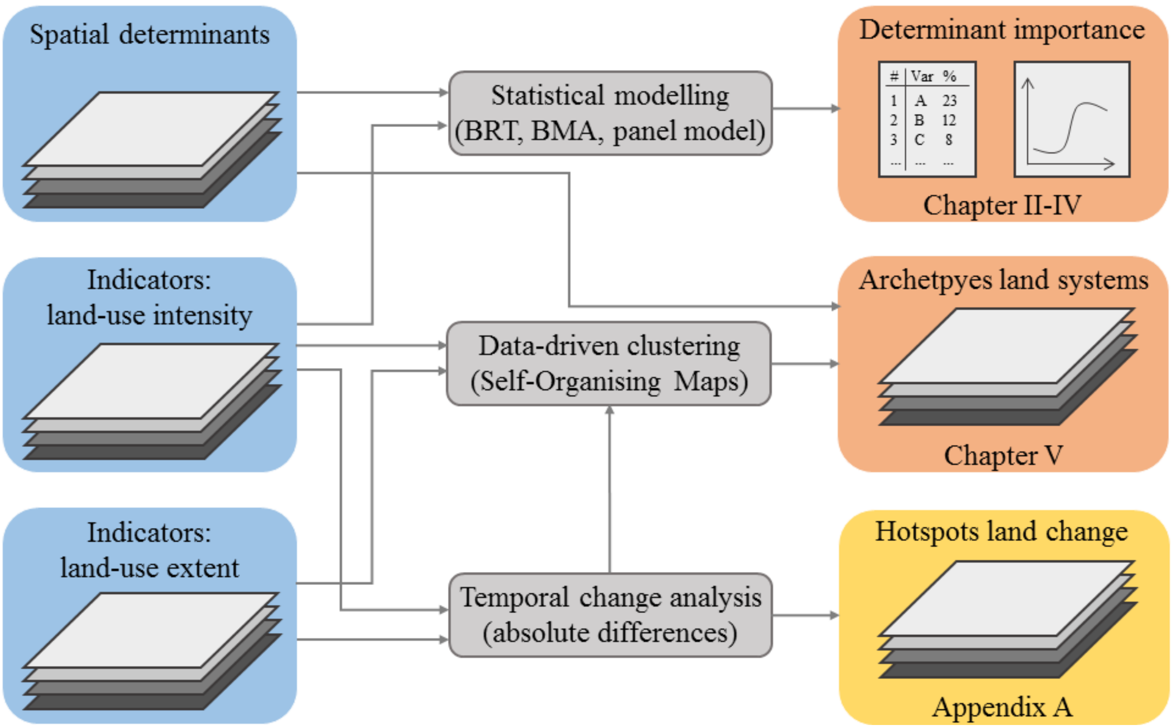

Figure I-1: Schematic overview of the workflow of this thesis. Data inputs in blue boxes, data processing and analyses in grey boxes, and results in orange (core research chapters) and yellow (appendix) boxes. For detailed descriptions of specific elements, please refer to sections 3.2 and 3.3 and to the respective chapters.

To answer *Research Question I*, three main objectives were required that each focus on a specific land-use class (i.e., forest or agriculture) and on different intensity indicators. Specifically, the objectives were to

(1) map patterns of forest harvesting intensity between 2000 and 2010 as a system metric of forest management intensity in Europe and identify its most important drivers,
(2) provide spatially explicit information on wood production between 2000 and 2010 as an output metric of forest management intensity in Europe,
(3) map patterns of yields and mineral nitrogen application as input and output metrics of agricultural intensity in Europe and identify their most important drivers.

The main objective to answer *Research Question II* was to

(4) map regions that show (i) similar land-system patterns in 2006 and (ii) similar trajectories of land-system change between 1990 and 2006 and to characterise these regions by a set of explanatory factors that are known to drive land-system change.

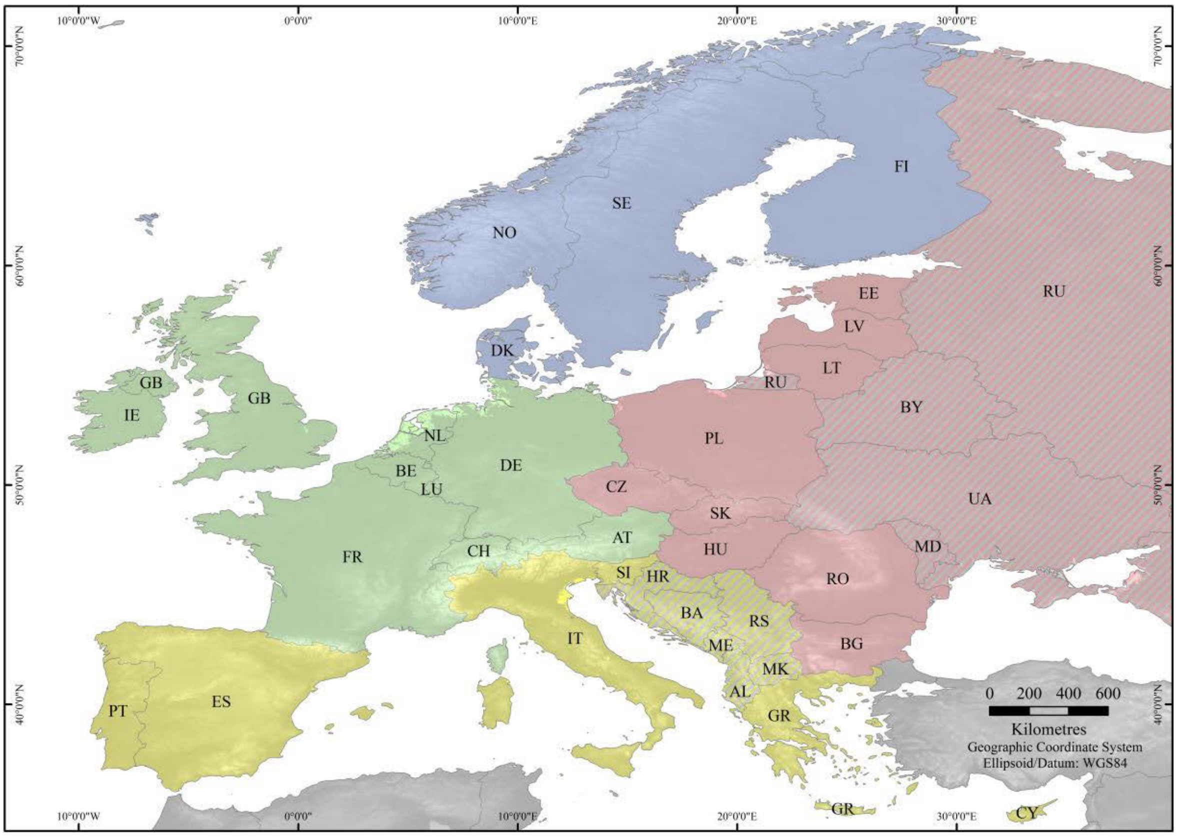

Figure I-2: Overview of the study area with topographic information and the classification of European sub-regions used in this thesis. Elevation ranges from 0m (whitish shading) to approximately 5,500m (greyish shading) a.m.s.l and was derived from Jarvis et al. (2008). Blue colouring indicates Northern European countries, green colouring Western European countries, red colouring Eastern European countries, and yellow colouring Southern European countries. Hatched areas belong to the respective sub-regions but were not addressed in this thesis. Bright colouring along coastlines represent areas below sea level.

The majority of analyses performed in this thesis focused on countries belonging to the EU27. In addition, for some analyses data for Norway and Switzerland were available and consequently used. For referring to the respective study area, the terms *EU27* and *Europe* (for the EU27 and additional countries) were used synonymously. Geographic descriptions and characterisations rely on a modified definition of the United Nations Statistics Division's classification of European sub-regions (UNSD 2013, Figure I-2).

3.3 Structure of this thesis

This thesis consists of six chapters: The introduction (Chapter I) is followed by four core research chapters (Chapter II-V) that relate to the objectives described above, and a synthesis that summarises the answers to the research questions, draws more general conclusions by identifying cross-cutting issues, and concludes by providing applications and an outlook for future research (Chapter VI). An additional appendix (Appendix A) supplements the information from Chapter II-V and contributes to address the research questions of this thesis. The five research chapters (see list below) were written as stand-alone manuscripts, which were either published in or submitted to international, peer-reviewed journals. Since each research chapter needed to meet the required structure for journal articles (i.e., introduction, material and methods, results, discussion, and conclusion), a thematic overlap between chapters has to be accounted for.

Chapter II *__Levers, C.__, Verkerk, P.J., Müller, D., Verburg, P.H., Butsic, V., Leitão, P.J., Lindner, M., and Kuemmerle, T. (2014). Drivers of forest harvesting intensity patterns in Europe. Forest Ecology and Management, 315, 160-172.*

This chapter provides information on spatial patterns of forest management intensity in Europe. Therefore, forest harvesting intensity was assessed on administrative unit level between 2000 and 2010 by calculating the felling-to-increment ratio to normalise wood production by ecosystem productivity. Furthermore, the most important spatial determinants that explain the spatial patterns of forest harvesting intensity were assessed using Boosted Regression Trees. Based on the outcomes of this study, candidate areas were highlighted where potentials for sustainable intensification of timber production may exist.

Chapter III *Verkerk, P.J.,* ***Levers, C.****, Kuemmerle, T., Lindner, M., Valbuena, R., Verburg, P.H., and Zudin, S. (2015). Mapping wood production in European forests. Forest Ecology and Management, 357, 228-238.*

This chapter provides spatially explicit (i.e., 1x1 km^2) information of wood production in Europe between 2000 and 2010. Dasymetric mapping was applied to disaggregate regional statistics on wood production based on two regression techniques (Bayesian Model Averaging and Boosted Regression Trees) and a suite of spatial determinants. Results improved traditional approaches relying on disaggregating wood production statistics by forest cover only.

Chapter IV ***Levers, C.****, Butsic, V., Verburg, P.H., Müller, D., and Kuemmerle, T. (in review). Drivers of changes in agricultural intensity in Europe. Agricultural Systems.*

This chapter assesses the patterns and most important spatial determinants of agricultural intensity changes on administrative unit level in Europe between 1990 and 2007. Time series of yields and mineral nitrogen application for six major crop type groups were used to represent the input and output dimension of agricultural intensity. Random effects panel regressions and a suite of spatial determinants were used to identify the most important factors related to changes in both intensity metrics and to assess their marginal effects.

Chapter V ***Levers, C.****, Müller, D., Erb, K., Haberl, H., Jepsen, M.R., Metzger, M.J., Meyfroidt, P., Plieninger, T., Plutzar, C., Stürck, J., Verburg, P.H., Verkerk, P.J., and Kuemmerle, T. (accepted). Archetypical patterns and trajectories of land systems in Europe. Regional Environmental Change.*

This chapter provides information on similar patterns and change trajectories of land systems in Europe between 1990 and 2006 as a first-order approximation of units within which similar, context-specific policies could be useful. Spatially explicit (i.e., 3x3 km^2) information of patterns and changes in land-use extent and intensity were used, together with socio-economic and environmental spatial determinants, to derive and characterise Land-System Archetypes and Archetypical Change Trajectories. Therefore, an automated clustering was performed using Self-

Organising Maps, which are highly suitable for reducing the complexity of spatial data due to their topology-preserving characteristics.

Appendix A *Kuemmerle, T.,* ***Levers, C.****, Erb, K., Estel, S., Jepsen, M.R., Kroisleitner, C., Müller, D., Plutzar, C., Stürck, J., Verkerk, P.J., Verburg, P.H., Reenberg, A. (in review). Hotspots of land use change in Europe. Environmental Research Letters.*

This chapter identifies hot- and coldspots of land-use change in Europe between 1990 and 2006 to demonstrate which regions underwent weak or strong changes for particular land-use categories. Spatially explicit (i.e., 3x3 km^2) information of changes in land-use extent and intensity were used to identify hot- and coldspots of land change by using data distribution cut-offs. Overlaying area and intensity changes for single land-use categories allowed for a more nuanced understanding of land-use changes. Summarising the abundance of changes allowed the identification and characterisation of regions that experienced few/many changes in parallel.

Chapter II:
Drivers of forest harvesting intensity patterns in Europe

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Abstract

Forests provide humankind with essential raw materials and the demand for these materials is increasing. Further expanding forestry into unmanaged forests is environmentally costly and increasing forest area via plantations will not immediately lead to increased wood supply. Thus, just like in agriculture, forestry faces the challenge how to intensify forest management in existing production forests in sustainable ways. Yet, our current understanding of what determines forest management intensity is weak, particularly at broad scales, and this makes it difficult to assess the environmental and social trade-offs of intensification. Here, we analyse spatial patterns of forest harvesting intensity as one indicator for forest management intensity across Europe, a region where most forests suitable for production are already in use and where future intensification is likely. To measure forest harvesting intensity, we related harvested timber volumes to net annual increment for the period 2000 to 2010. We used boosted regression trees to analyse the spatial determinants of forest harvesting intensity using a comprehensive set of biophysical and socioeconomic explanatory variables. Our results show that forest harvesting intensity varied markedly across Europe and harvested timber volumes were well below the increment in most regions. Harvesting intensity was especially high in southern Finland, southern Sweden, south-western France, Switzerland, and the Czech Republic. The spatial patterns of forest harvesting intensity were well explained by forest-resource related variables (i.e., the share of plantation species, growing stock, forest cover), site conditions (i.e., topography, accessibility), and country-specific characteristics, whereas socioeconomic variables were less important. We also found the relationship between forest harvesting intensity and some of its predictors (e.g., share of plantation species, accessibility) to be strongly non-linear and characterized by thresholds. In summary, our study highlights candidate areas where potentials for sustainably intensifying timber production may exist. Our analyses of the spatial determinants of harvesting intensity also provides concrete starting points for developing measures targeted at increasing regional wood supply from forests or lowering harvest pressure in regions where forests are heavily used. Finally, our study emphasizes the importance for systems' understanding for designing and implementing effective sustainable forest management policies.

1 Introduction

Land use provides humanity with essential food, fibre, and bioenergy, but is also a major force of global environmental change (MA 2005a, Haberl et al. 2007, Pereira et al. 2010). As fertile land is getting scarce (Lambin and Meyfroidt 2011) and further expansion of land use into remaining wildlands incurs high environmental costs, future production increases will, to a large extent, have to rely on sustainably intensifying land already in use (Foley et al. 2011, Tilman et al. 2011). Yet, assessing where future production can be increased and understanding the trade-offs of intensification is currently limited by incomplete knowledge about the spatial patterns and drivers of intensification pathways, especially at broad geographic scales (Verburg et al. 2009, Erb 2012, Lambin et al. 2001).

This is particularly the case in forestry, where the spatial patterns of forest management intensity and the drivers that produce these patterns remain highly unclear. This is unfortunate, because forest management effects on forest ecosystem functioning vary substantially depending on management intensity. For example, the intensity by which forests are managed affects forest structure (Vilén et al. 2012), soils (Jandl et al. 2007), biogeochemical cycles (Nabuurs et al. 2013, Luyssaert et al. 2012), biodiversity (Paillet et al. 2010), and ecosystem service provisioning (Gamfeldt et al. 2013). Understanding the spatial patterns of forest management intensity and its drivers is therefore important for assessing the environmental trade-offs of forestry and for identifying opportunities for sustainable intensification.

Assessing forest management intensity is challenging because intensity itself is a complex term, encompassing multiple dimensions (Schall and Ammer 2013). Consequently, forest management intensity has been examined using a wide range of indicators, including harvested timber volumes, forest structural parameters (e.g., the difference between potential and actual biomass storage), stand establishment practices, tree species composition, length of rotation periods, human appropriated net primary production, or the amount of fertiliser, herbicides, and machinery used (Luyssaert et al. 2011, Forest Europe et al. 2011, Duncker et al. 2012). Intensity metrics, which relate inputs (e.g., capital), outputs (e.g., harvested timber volumes), or system properties (e.g., ecosystem productivity) to each other, can provide insights into land use intensity patterns and drivers (Erb et al. 2013a, Kuemmerle et al. 2013). For example, interpreting harvested timber volumes without considering ecosystem productivity could be misleading as the same volume of timber extracted from forest systems with high or low productivity may indicate very different levels of forest harvesting intensity. By expressing harvested timber volumes in relation to the net annual increment, forest harvesting intensity can be assessed across large regions.

Unfortunately, studies assessing forest harvesting intensity have either focussed on the national scale (e.g., relying on national forest resource assessments, (Kuusela 1994, Forest Europe et al. 2011)), or on small study regions (see Schall and Ammer 2013 for an overview), both of which precludes understanding spatial patterns of management intensity. Only two studies addressed drivers of forest harvesting patterns at broad spatial scales. Analysing timber harvesting patterns in European Russia showed that road density, forest composition, and total forest area were important determinants of harvesting patterns (Wendland et al. 2011). A range of spatial variables including tree species composition, slope, forest coverage, proximity to cities, and conservation areas allowed mapping different forest management systems in Europe using an expert-based approach (Hengeveld et al. 2012). We know of no study explicitly addressing broad-scale patterns of forest harvesting intensity.

Evidence on the drivers of forest owner's decisions to manage their forest intensely or not was only derived from local-scale case studies. These studies, mainly focussing on non-industrial, private forest owners, show that a range of policy, forest resource, and market factors are potentially important in determining timber volumes extracted (Beach et al. 2005, Amacher et al. 2003). For example, forest management plans, property size, and income from agriculture determined harvesting decisions in Norway (Størdal et al. 2008), ownership size and type shaped harvesting decisions in the southern US (Arano and Munn 2006), or the demand for wood products and associated price changes were important drivers of harvesting decisions in the US and Australia (Adams et al. 1991, van Putten and Jennings 2010). Furthermore, population density, forest size, and distance to urban areas influenced harvesting in the US (Wear et al. 1999, Munn et al. 2002). Yet, none of these studies addressed patterns and drivers of forest harvesting intensity for larger regions. Clearly, there is a research gap at the regional scale, which is unfortunate because of its major importance for policy making and for mitigating the impacts of global environmental change (Wu 2013).

Regression models are powerful tools to assess drivers and determinants of land use patterns (Müller et al. 2011, Baumann et al. 2011, Wendland et al. 2011). Algorithmic models are particularly promising because they do not impose any a-priori relationship between target and predictor variables. Fewer requirements on the data structure make them well-suited to investigate the complex and often non-linear interactions between predictors and response in land systems. Algorithmic models, such as boosted regression trees (BRT), generally attain a higher model fit and predictive accuracy than traditional statistical approaches (Elith et al. 2006, Lakes et al. 2009, Lin et al. 2011). Because of their higher predictive accuracy, better ability to generalise from data, and possibility to handle large heterogeneous data sets, algorithmic models are gaining growing attention in ecology (Leathwick et al. 2006, De'ath and Fabricius 2000) and land change science (Müller et al. 2013, Gellrich et al. 2008), but no study has so far used BRTs to assess spatial determinants of forest harvesting intensity.

In this study, we sought to quantify and understand broad-scale spatial determinants of forest harvesting intensity patterns across the European Union (EU-27) plus Norway and Switzerland. As intensity metric, we used the ratio of harvested timber volume (fellings and harvest losses) and net annual increment volume (hereafter referred to as "forest harvesting intensity") because this ratio is an important criterion to assess the sustainability of forest resource use. As explanatory variables, we focused on selected factors that are indirect proxies of the underlying drivers of forest harvesting intensity (hereafter referred to as "spatial determinants").

Europe is an interesting case for assessing forestry intensity since forest use in Europe has a long history. After centuries of extensive deforestation, Europe's forests increased in the 19th and 20th century as a result of farmland abandonment, afforestation, and nature protection (Kaplan et al. 2012, Rudel et al. 2005), and forests now cover 37% of Europe's terrestrial surface. Though forest cover has increased steadily during the last decades (0.37% per year, Forest Europe et al. 2011), forest harvesting intensity also remarkably increased from 58% (1990) to 62.4% (2010) and is expected to increase further (UNECE and FAO 2011, Böttcher et al. 2012). Forest cover is distributed very unevenly across Europe and the region is furthermore characterised by large environmental (e.g., boreal to Mediterranean), historical (e.g., capitalism vs. socialism), ethnic, and economic (highly industrialised vs. less industrialised economies) heterogeneity. How this heterogeneity relates to spatial patterns in forest harvesting intensity remains largely unclear. Understanding forest harvesting intensity is one key aspect for assessing forest management intensity. To ensure the sustainable intensification of forest management in light of growing demands for timber products would, however, require a range of indicators addressing the multidimensionality of forest management intensity.

We compiled time series of sub-national forest harvesting intensity patterns in Europe between 2000 and 2010 and used boosted regression trees to quantify the influence of a set of biophysical, infrastructure, and socioeconomic variables in shaping these patterns. Specifically, we ask the following research questions:

1. What are the spatial patterns of forest harvesting intensity in Europe?
2. What are the most influential spatial determinants of these patterns and what is their relative importance?
3. What is the nature of the relationships between forest harvesting intensity and its spatial determinants?

2 Material and methods

2.1 Data

Forest harvesting intensity

To estimate forest harvesting intensity, we collected sub-national forest harvesting statistics [m^3/ha], net annual increment [m^3/ha], and forest area [ha] from national forestry reports, statistical yearbooks and databases, and by contacting national experts. Statistics were collected for the entire EU-27 plus Norway and Switzerland and – when possible – for each year between 2000 and 2010 (see Table SI II-1 to for a full list of references). Data were collected for administrative units ranging from the national scale (for small countries) to the district level (for large countries), with 1 to 107 regions representing a single country (see Figure II-1 in the *Results and Interpretation* section). We excluded six regions with major data gaps resulting in 454 administrative units that were used for subsequent analysis.

The dataset was harmonised to correct for differences in national harvesting definitions (e.g., harvesting volume over or under bark, in- or exclusion of harvest losses). To do so, we calculated the annual volume share per region in the total harvest volume for a particular country based on the regional statistics, and used those shares to subdivide national-level, harmonised harvest data representing roundwood removals (m^3) under bark and fuelwood (FAOSTAT 2012). Data for some regions (see Table SI II-1) were missing for certain years and we then assumed an identical volume share of the national harvest levels for the closest years where data were available. The same data collection and harmonisation steps were repeated for statistics concerning net annual increment (NAI) and forest area (see Table SI II-2 and Table SI II-3), which were harmonised with reported increment levels and forest area for the year 2000 (Forest Europe et al. 2011) to correct for differences in national harvesting definitions. To facilitate the comparison of forest harvest intensity across years, we used the average net annual increment for the period 2000-2010. To convert wood removals to fellings, we added bark (Forest Europe et al. 2011; UNECE and FAO 2010) and stem harvest losses (UNECE and FAO 2000). Based on these data, we calculated the volume of wood fellings and NAI and subsequently forest harvesting intensity (as a percentage) for the period 2000-2010.

Predictor variables

We reviewed studies investigating harvesting decisions to identify a set of variables potentially influencing forest harvesting intensity. The reviewed studies were mostly conducted on local to regional scale and we assumed that the influence of the identified variables on forest harvesting intensity found by these studies would potentially also apply at the pan-European scale. Due to the deductive and exploratory character of our study, we did not impose any ranking of a variables' influence, whereas the general type of relationship between variable and forest harvesting intensity was hypothesized a priori (Table II-1; see Text SI II-1 for the rationale behind selecting the variables used in our analyses and detailed information on the sources of these variables). We identified 23 predictor variables that we hypothesise to potentially influence forest harvesting intensity in Europe. We grouped the predictor variables – except the country dummy – into three main groups: (i) forest resource variables, (ii) environmental conditions, and (iii) other socioeconomic variables. Thirteen variables were available as raster layers, the majority with a 1x1 km² native resolution. We re-projected all raster layers into the Lambert Azimuthal Equal Area projection and used bilinear interpolation to resample growing stock and ruggedness data from their native resolutions to the 1x1 km² target resolution. Subsequent to the harmonisation of predictors, we aggregated these variables to the administrative units of the target variable. Therefore, we weighted data related to non-forest land covers with a continuously scaled forest cover map to represent forested areas more prominent when calculating average values for the utilised administrative units.

Table II-1: Description of single predictors, their measurement units, resolutions (*Res*), data sources, descriptive statistics, spearman correlations (*Corr*) and expected relations (*Sign*) with forest harvesting intensity, and data formats (*Format*). Descriptive statistics were calculated for numeric variables only. Symbols for *Sign* indicate whether predictor increases go along with increases (+) or decreases (-) in forest harvesting intensity or no explicit relationship (•). Abbreviations in the column *Format* are: R – raster, V – vector, S – static, and D – dynamic. Time-variant variables are marked with an asterisk and their descriptive statistics were calculated with averaged values.

Factor	*Predictor name*	*Descrip-tion*	*Unit*	*Res*	*Source*	*Mean*	*SD*	*Corr*	*Sign*	*Format*
Forest resources	BEECH-OAK	Share of beech (Fagus spp.) and oak (Quercus spp.) in total species	%	1km	Brus et al. 2012	22.3	18.6	-0.1	+	R,S
	FCOV	Forest cover of Europe	%	1km	Pekkarinen et al. 2009, Schuck et al. 2002	34.6	18.7	0.1	+	R,S
	PINE-SPRUCE	Share of pine (Pinus sylvestris) and spruce (Picea spp.) in total species	%	1km	Brus et al. 2012	29.9	28.4	0.4	+	R,S
	PLAN-TATION	Share of plantation species (Robinia spp., Populus spp., Eucalyptus spp., Pinus pinaster) in total species	%	1km	Brus et al. 2012	6.6	10.0	-0.3	+	R,S
	TOTPROT	Share of protected forest in total forest	%	1km	IUCN and UNEP-WCMC 2012; EEA 2011	19.1	19.0	-0.1	-	R,S
	TOTVOL	Total growing stock	$m3\ ha^{-1}$	500 m	Gallaun et al. 2010	154.2	70.4	0.3	+	R,S
Environmental conditions	POOR-SOIL	Share of low productive soil limiting growth	%	1km	Driessen et al. 2001; EC 2006b, Verkerk et al. 2011	11.1	16.6	-0.2	-	R,S
	PRCP5M	Precipitation sums of growing season	mm	1km	Hijmans et al. 2005	330.4	106.6	0.0	+	R,S
	RUGG	Terrain ruggedness expressing relief energy	m	1km	NASA 2006; Riley et al. 1999	68.1	62.0	-0.4	-	R,S
	SBC	Share of soil types with no bearing capacity	%	1km	EC 2006b, Verkerk et al. 2011	8.0	13.8	0.2	-	R,S
	TEMP	Long term mean temperature	°C	1km	Hijmans et al. 2005	8.5	3.2	-0.3	+	R,S
	WAT-SHORT	Difference of precipitation and potential evapo-transpiration during growing season	mm	1km	New et al. 2002, Metzger et al. 2005b, Hijmans et al. 2005	-27.2	39.0	0.1	-	R,S
	COUNTRY	Dummy to capture country attributes	-	•	Own calculation	NA	NA	NA	•	V,S

Socio-economy	ACC50	Travel time to cities > 50,000 inhabitants	min	1km	Nelson 2008	137.4	84.6	-0.2	•	R,S
	FAOintens*	1yr time lag felling-to-increment ratio	%	•	Table SI II-1 - Table SI II-3	64.0	52.1	NA	+	V,D
	GDP PPS*	1yr time lag gross domestic product	%	•	EC 2015c	19049	7938	-0.1	+	V,D
	GVAprim*	1yr time lag gross value added in I. sector	%	•	EC 2015c	457.2	948.3	0.1	+	V,D
	JOBLESS*	1yr time lag jobless ratio	%	•	EC 2015c	8.2	3.9	0.1	•	V,D
	LABOUR prim*	1yr time lag labour force in I. sector	%	•	EC 2015c	32.9	62.4	0.0	+	V,D
	OIL*	1yr time lag heating oil prices incl. tax	%	•	EC 2013b	751.3	202.3	-0.2	+	V,D
	PRIVFOR	Share of privately owned forest	%	•	Pulla et al. 2013	59.4	26.0	-0.1	+	V,S
	TIMBER*	1yr time lag timber prices	%	•	FAOSTAT 2012	82.2	22.1	-0.4	+	V,D
	URBRUR	Urban-rural typology	-	•	EEA 2010	NA	NA	NA	•	V,S

To do so, we used the forest map by Pekkarinen et al. (2009), which we calibrated to match regional-and national-level forest area statistics as described in section 2.1 using the approach developed by Schuck et al. (2002). We then calculated the percentage change for one-, three-, and five-year periods for the socioeconomic variables that were available as annual time series on the utilised administrative units and merged them with the aggregated spatial data.

2.2 Boosted regression trees

We used boosted regression trees (BRTs) to quantify the influence of a set of spatial determinants in shaping forest harvesting intensity patterns in Europe. BRTs evolved in the tradition of machine learning techniques and belong to the family of non-parametric models. The most important difference to statistical approaches is that machine learning techniques are distribution-free (i.e., no a-prior assumptions on the distribution of the target variable or explanatory variables are made). Machine-learning techniques assume independent observations and that the process generating the data is complex and unknown, and therefore use an algorithm to learn the relationship between a target variable and explanatory variables (Breiman 2001b, Elith et al. 2008). BRTs build upon decision trees, which explain the variance of a target variable by splitting up the variable space into rectangles in a binary fashion. A simple model (constant) is fitted to each partition by fitting the mean response for observations in that partition (Elith et al. 2008, Hastie et al. 2011). From the suite of available predictors, BRTs select those that minimise the prediction errors. This is the main difference to Random Forest models, where a random feature selection is applied before fitting individual trees (Breiman 2001a). Contrary to decision trees with a single but potentially complex decision tree, BRTs use many simple decision trees in an ensemble (i.e., boosting). Boosting is a numerical optimisation technique that minimises the loss function of a model by adding trees in a forward stage-wise fashion (i.e., existing trees remain unchanged when more trees are added; only the fitted value is re-estimated). The first tree maximally reduces the loss function, whereas all following trees focus on the residuals of the previously fitted model, hence explicitly on the unexplained variance in the target variable (Elith et al. 2008). This leads to drastically increased predictive accuracy (Hastie et al. 2011, Friedman et al. 2000). BRTs do not tend to overfit because they introduce stochasticity by randomly withholding a certain percentage of the data while fitting the model (Dormann et al. 2013). Furthermore, BRTs are robust against missing data and collinearity of predictors while being able to handle non-linear relationships and interaction effects (Hastie et al. 2011, Elith et al. 2008). However, for interpreting the results, knowledge on the correlation structure between the predictors is beneficial which is depicted in Figure SI II-2 in the Supplementary Information. Interaction effects reinforce the shared influence of two predictors compared to decision trees with no variable interactions. Assessing the nature and magnitude of possible interaction effects yields a better understanding of the investigated phenomenon (Elith et al. 2008).

Generally, BRTs combine high predictive accuracy with good interpretability of results (Friedman 2001), making them a preferable tool to investigate the spatial determinants of forest harvesting intensity. The calibration of BRTs necessitates specifying four main parameters: (i) number of trees (*nt*), (ii) tree complexity (*tc*), (iii) learning rate (*lr*), and (iv) bag fraction. The number of trees defines how many single decision trees are used in the model, tree complexity defines the maximum allowed interaction levels between predictors, the learning rate scales the contribution of each single decision tree to the entire BRT model, and the bag fraction defines the share of data that is withheld from the training data while fitting each single decision tree. A detailed mathematical introduction to BRTs is provided by Hastie et al. (2011) and a hands-on tutorial by Elith et al. (2008).

To explain the spatial determinants of forest harvesting intensity patterns, we carried out two analyses: First, we fitted a static model using the average forest harvesting intensity over the study period (2000-2010) as response and all static variables and averages of time-variant predictor variables as predictors. This model allows for the assessment the general spatial determinants of forest harvesting intensity patterns across Europe. Second, we fitted ten annual models, one for each year, using the annual time series of the target variable (from 2001 to 2010) as response and all static variables, change ratios of time-variant predictor variables, as well as the time lags of the target variable as predictors. Change ratios and time lags were tested for one-, three-, and five-year time periods separately. These time-variant models expand the static approach by insights into changes in the relative importance of predictor variables over time. Combining the model results yields a comprehensive understanding of static and time-variant spatial determinants of forest harvesting intensity in Europe.

We used the *dismo* package (Hijmans et al. 2013) in R (R Development Core Team 2012) to perform all analyses. Different parameter settings might influence model performance and we therefore conducted a systematic sensitivity analysis to test all combinations of interaction levels from 1 to 9 and learning rates from 0.1 to 0.001 to identify optimal parameter settings for subsequent analyses by using 10-fold cross-validated correlation coefficients. To avoid stochastic bias, we calculated row and column averages and selected the parameter combination with the highest values for *tc* and *lr* (Table SI II-4). Lower learning rates were also tested but revealed model impairments and drastically increased computation time (results not shown). As a result of the sensitivity analysis, we chose an interaction level of 4 and a learning rate of 0.0025. For each model iteration we randomly withheld 50% of the full data set (without replacement) to fit the model. The number of trees was automatically determined by using the *gbm.step* routine provided by the *dismo* package. We did not exclude extreme values of forest harvesting intensity since BRTs are insensitive to outliers (Elith et al. 2008). Only variables with a relative contribution above that expected by chance (100%/number of variables; static: 100%/22 = 4.55%, dynamic: 100%/23 = 4.35%) were interpreted (Müller et al. 2013). We used partial dependency plots (PDPs) to investigate the relationship between each predictor and the target variable. PDPs depict a variable's influence along its data range while holding all other variables at their mean (Friedman 2001). To enhance interpretability, all plots were smoothed using a spline interpolation except for categorical variables. To compare variable rankings for the time-variant model we calculated Kendall's *tau* (Kendall 1938). We used the Moran's I measure of spatial autocorrelation (Moran 1950) to investigate spatial clustering of forest harvesting intensity and model residuals. Moran's I values range from -1 (negative autocorrelation; dissimilar objects tend to cluster) to 1 (positive spatial autocorrelation; similar objects tend to cluster).

3 Results and interpretation

3.1 Patterns of forest harvesting intensity

The spatial patterns of average harvested timber volumes on the one hand, and our forest harvesting intensity index on the other hand differed substantially (Figure II-1). For example, southern Germany had generally high harvested volume levels (i.e., harvested timber volume per hectare forest), but relatively low forest harvesting intensity due to high forest productivity, whereas in southern Finland high forest harvesting intensity occurred despite lower harvest levels. Generally, harvested timber volumes are correlated with the productivity of forests, which is, to a large extent, explained by environmental conditions. Hence, patterns in harvested timber volumes do not linearly translate into forest harvesting intensity, highlighting the potential usefulness of our intensity measure.

Forest harvesting intensity also varied markedly across Europe (Figure II-1a) and showed moderate spatial clustering (static: Moran's I = 0.342; time-variant: avg. Moran's I = 0.321, SD = 0.063), i.e. that high forest harvesting intensity in one place is associated with high forest harvesting intensity in neighbouring spatial units. Generally, an increase in forest

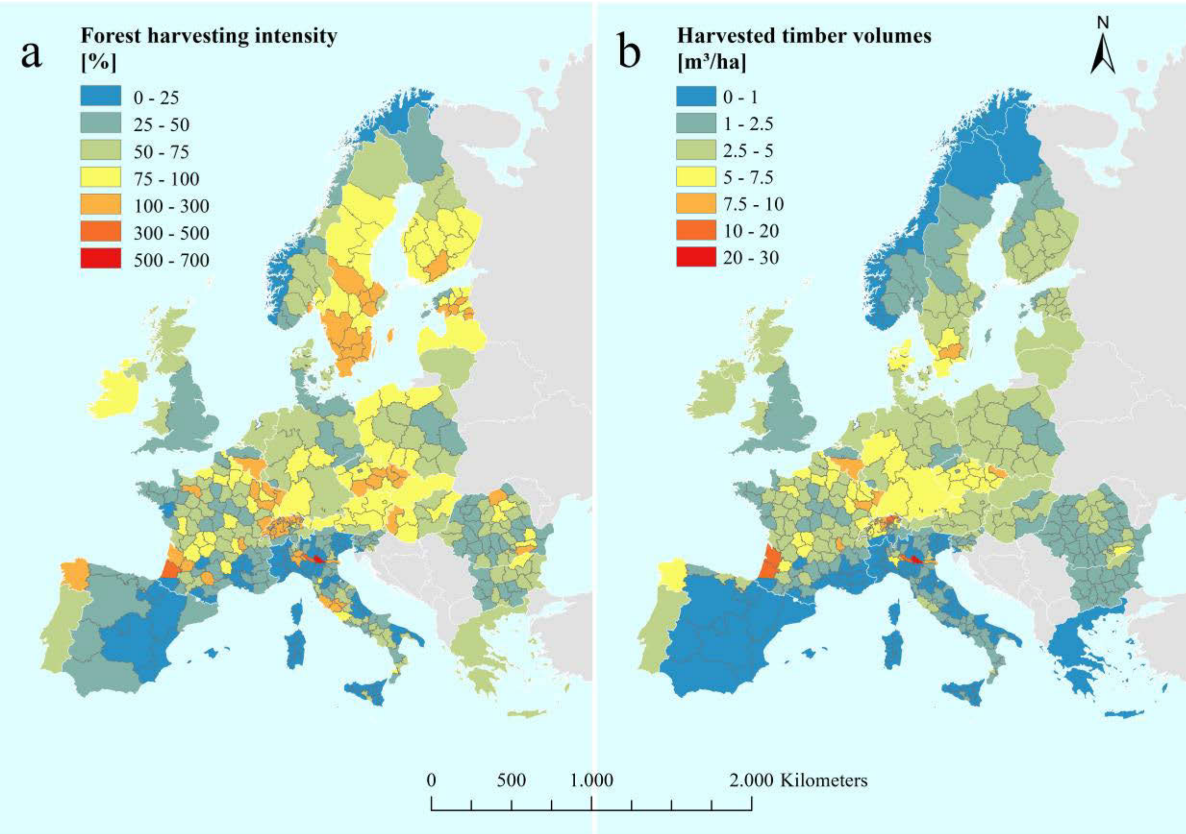

Figure II-1: European administrative units (NUTS0-3) showing average forest harvesting intensity [%] (a) and average harvested timber volumes [m^3 ha^{-1}] (b) for 2000-2010.

harvesting intensity was observable for Central Europe during the study period, whereas the intensity level of Scandinavian and Mediterranean countries remained largely constant (Figure SI II-1). Averaged over the period 2000-2010, regions with high forest harvesting intensity occurred in the southern parts of Finland, Sweden, Estonia, Czech Republic, as well as in Switzerland and smaller areas of northwest Spain, southwest and eastern France, and some scattered regions in Italy. Harvested timber volumes exceeded increment volumes substantially in some of these regions, for example, in southern Sweden and southwest France. Both, southern Sweden and the southwest of France suffered from severe storm events in the study period. Hence, subsequent salvage logging could explain high forest harvesting intensity.

3.2 Model performance

The static BRT model explained 55% of the variation in forest harvesting intensity patterns, the time-variant models yielded on average an explanatory power of 42% (SD = 5.02%), as all time-variant models had a lower performance than the static model (Table II-2). Interestingly, incorporating time-variant predictors did not substantially improve model performances. Reasons for this might be time lags larger than the study period or the lack in quality of the utilised socioeconomic factors such as timber prices. Another reason might be the fact that, due to long rotation length, forest harvesting intensity generally does not strongly depend on annual changes but rather on static environmental and socioeconomic conditions. We observed an exceptionally low model performance in 2006 being more than two standard deviations lower than the average over the study period. A possible explanation might be that the storm Gudrun in 2005 significantly disturbed forest

Table II-2: Training and validation performance for all models.

MODEL SUMMARY	YEAR										
	2001	*2002*	*2003*	*2004*	*2005*	*2006*	*2007*	*2008*	*2009*	*2010*	*Static*
# trees	5430	2870	2490	2850	2530	5440	1830	5560	4440	3750	6110
CV r	0.68	0.63	0.66	0.64	0.64	0.54	0.64	0.66	0.66	0.70	0.74
CV r^2	0.46	0.40	0.44	0.42	0.41	0.29	0.41	0.44	0.44	0.49	0.55
Train r	0.90	0.85	0.85	0.87	0.86	0.91	0.78	0.93	0.90	0.90	0.93
Train r^2	0.81	0.72	0.72	0.76	0.74	0.83	0.61	0.86	0.81	0.81	0.86
Mean total dev.	3416	2936	2281	2361	2897	7837	2688	3220	3513	3058	2708
Mean residual dev.	722	939	689	651	861	2034	1138	522	752	657	447
CV std. error	0.04	0.04	0.03	0.02	0.05	0.09	0.04	0.05	0.06	0.04	0.03
Est. cv dev.	1937	1858	1339	1487	1975	5765	1828	1654	1851	1590	1305
Est. cv dev. std error	642	656	249	421	741	2354	711	352	519	399	492

management schemes. Heavy salvage logging could have led to large timber stocks, which made forest harvesting unnecessary in the subsequent year. Figure SI II-1 supports this assumption showing that almost entire Sweden showed higher forest harvesting intensity in 2005 compared to the previous years, followed by a drastic drop in 2006. Adaptations of forest management schemes along with negative trends in local roundwood prices as a consequence of destructive storms (Gardiner et al. 2010) may not be captured by the data and could have resulted in lower model performance in the year 2006. Model residuals did not reveal any distinct patterns of spatial autocorrelation (static: Moran's I = 0.044; dynamic: avg. Moran's I = 0.056, SD = 0.031) indicating good model specification and agreement with the independent error assumption (Crase et al. 2012).

3.3 Variable importance in the static model

The results of the static BRT model showed that the share of plantation species, terrain ruggedness, and country-specific characteristics contribute together to more than half of the model's explained variance (Figure II-2, see Table SI II-5). Additional forest-related variables (growing stock, forest cover, share of pines and spruces) and accessibility also contributed considerably while most socioeconomic variables exerted little effect on forest

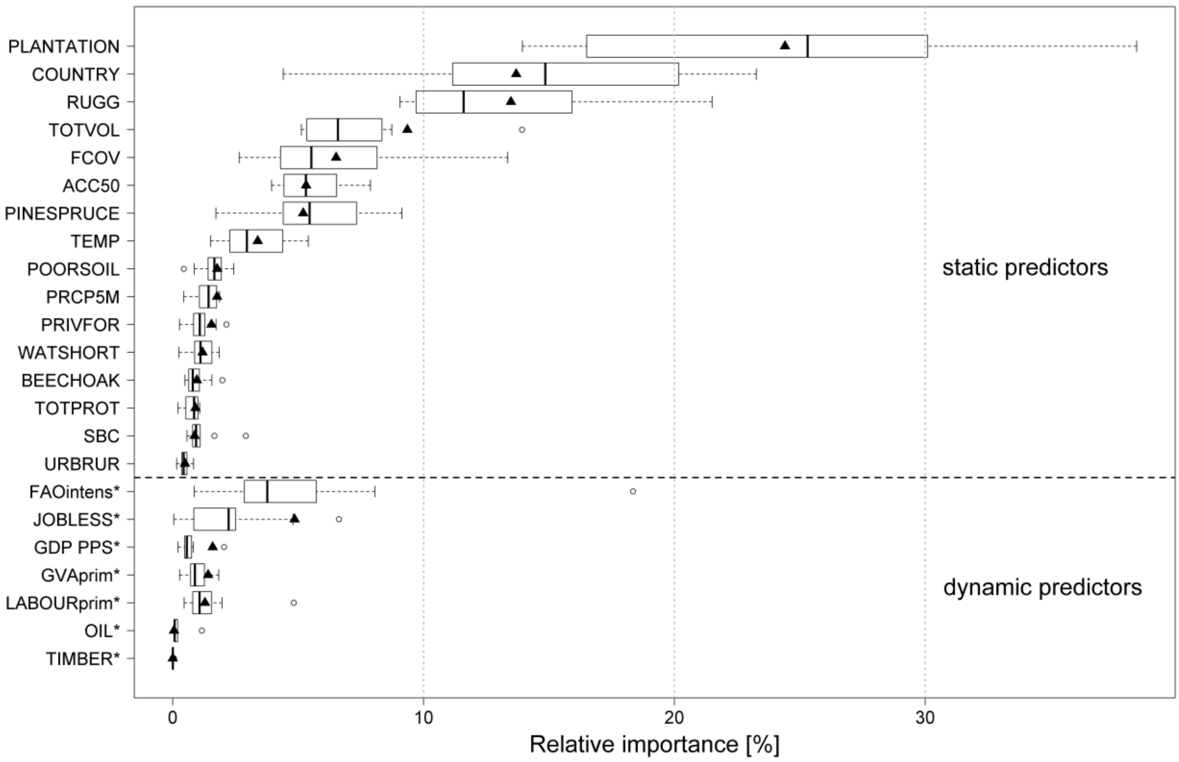

Figure II-2: Relative importance of predictors for the static (solid triangles) and time-variant (boxplots) model. Time-variant variables are marked with an asterisk and were averaged in the static model. In the time-variant model, one-year change ratios of the respective variables were used. Please refer to Table II-1 for explanations of the variables.

harvesting intensity except for jobless ratio. Country-specific characteristics were important and suggest that much of the remaining unexplained variance were due to country-level variations not captured by the data. Environmental conditions such as temperature, precipitation, or soil quality, did not influence forest harvesting intensity significantly, possibly because our harvesting intensity index already controlled for a large share of productivity effects which are important determinants of ecosystem productivity and thus increment.

Figure II-3 displays the PDPs of all predictors selected for interpretation (see section 2.2). The share of plantation species was the most important variable for explaining forest

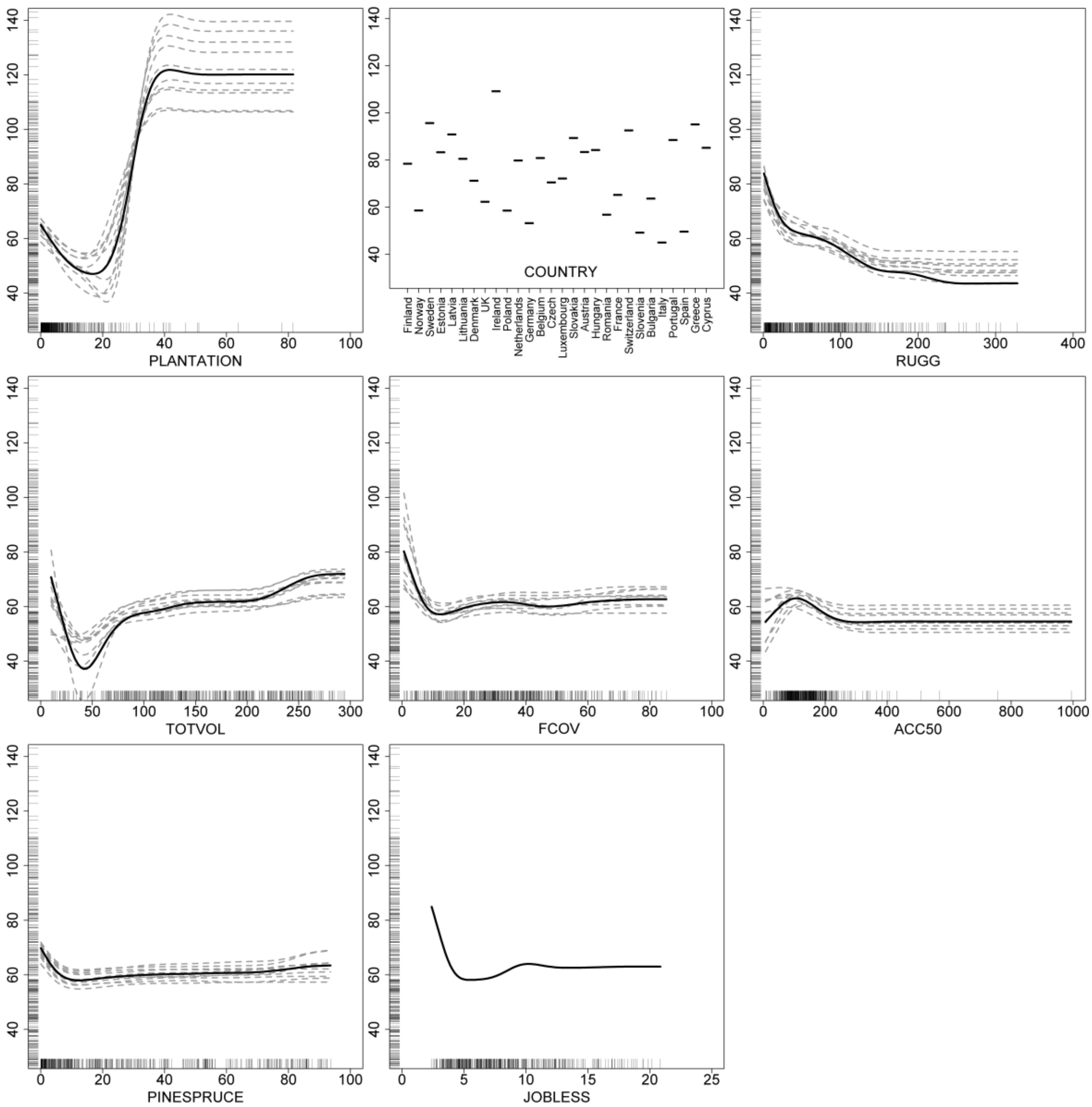

Figure II-3: Partial dependency plots (PDPs) for the eight most influential variables. The black, bold line represents the results from the static model, the dashed, grey lines the results for each year of the time-variant model. The vertical axis of the PDPs shows fitted values for each observation along the variable's data range displayed on the horizontal axis. Both axes are equipped with rug plots that visualise the distribution of the respective data space in percentiles. For JOBLESS*, only the average value is displayed since change ratios were used in the time-variant model resulting in a disagreement of units.

harvesting intensity. After an initial decline in predicted forest harvesting intensity, intensity drastically increases beyond a threshold of 20% plantation species cover and saturates beyond 40% at an intensity of 100% – 140%. This indicates that all regions with plantation cover beyond this critical value were predicted to be intensively harvested, whereas regions with plantation forest below the threshold were all managed at relatively lower intensity. A possible explanation for the initial decrease could be that plantation species occur either in sparsely forested areas or only infrequently in unmanaged forests consisting of different, non-industrial tree species. In both cases, harvesting of plantation species is unlikely. Scrutinising the spatial patterns of forest harvesting intensity and plantation species cover clearly reveals that intensive monoculture plantations constitute an important anthropogenic modification of forest ecosystems (Hartley 2002) and that such intensively managed forests are concentrated in a few regions in Europe (e.g., in the Mediterranean countries, western France, and Romania, Figure II-4a). Plantation species, which are typically managed with short rotation cycles (see Text SI II-1 in the Supplementary Information), are logically related to high forest harvesting intensity, as

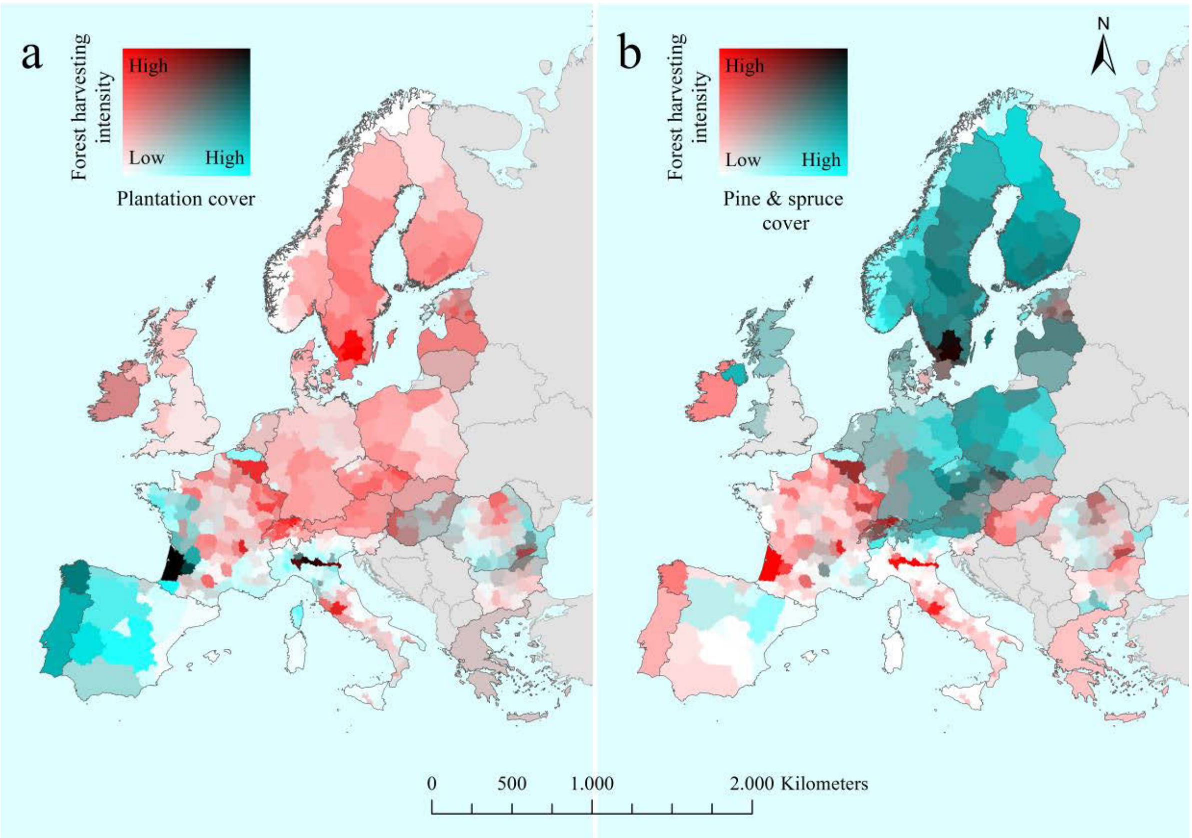

Figure II-4: Overlay map of forest harvesting intensity and plantation cover (a) and pine and spruce cover (b). All three variables were z-transformed for comparability. Bright blue colours indicate high tree species (plantation, pine and spruce) coverage, bright red colours indicate high forest harvesting intensity, white indicates low values for both plot variables, and black indicates high values for both plot variables.

their occurrence is often caused by silvicultural measures with the intention of timber or biomass production. Interestingly, these areas are often not intensely managed with regard to our forest harvesting intensity measure, except for a few areas in western France and northern Italy. In contrast, high forest harvesting intensity occurred in Central and Eastern Europe, Scandinavia, and the Baltic countries where plantation coverage is low.

The second-most important variable in our model were country-specific differences in policies and socio-economics, captured by the country dummy. The influence of country-specific characteristics varies from predicted forest harvesting intensity of 40% in Italy to almost 120% in Ireland. High values of predicted forest harvesting intensity suggest that other predictors did not capture country-specific information. For example, in Ireland, Sitka spruce (*Picea sitchensis*) is an important forestry species (Department of Agriculture Food & the Marine s.a.). However, the tree species map (Brus et al. 2012) does not distinguish between different spruce species (*Picea spp.*). Generally, country specific characteristics can capture differences in forest legislations and policies, traditions in forestry, differences in forest ownership structure, forest definitions, or fire and storm events, which all strongly shape forest harvesting intensity but could not be explicitly derived as explanatory variables.

Terrain ruggedness was the third-most important variable and forest harvesting intensity decreased with increasing ruggedness. Forest harvesting intensity was only half for regions with high relief energy, particularly for regions exceeding a ruggedness of 20m. Strong ruggedness arguably limits forest harvesting intensity because costs of timber extraction increase (Simões and Fenner 2010, Hengeveld et al. 2012). The fourth-most important variable was the total volume of growing stock and forest harvesting intensity increased with increasing biomass availability (Hengeveld et al. 2012). However, regions with less than 50 m^3/ha show decreasing forest harvesting intensity with increasing growing stock volume, which may be due to low productivity or low or fragmented forest cover.

Forest cover was the fifth-most important variable and low forest cover co-occurred with lower predicted forest harvesting intensity. The explanation for this is straightforward since intensive harvesting can be done most efficiently in large forest patches (Hengeveld et al. 2012). The sixth-most important variable was accessibility. Our results showed an initial increase of forest harvesting intensity with increasing travel time to cities until it peaked at a travel distance of 60-90 minutes. Beyond this point, harvesting intensity decreased and finally levelled off at a distance of approximately 240 minutes. A reason for this humpshaped relationship between accessibility and forest harvesting intensity could be that forests close to urban areas may have other functions (e.g., recreation), which could reduce logging activities in these areas (van Berkel and Verburg 2011), thus providing support for the importance of urban-hinterland teleconnections (Seto et al. 2012). Another reason might be the negative impacts of transport systems. Large forest industry facilities require many transport movements, which are not wanted in or close to urban areas. Furthermore, a shortage of resources (more agricultural areas in the vicinity of cities) and environmental impacts (e.g., odours from pulp and paper mills) may prevent high intensive use of forests near urban areas.

Long-rotation coniferous species (rank 7) and jobless ratio (rank 8) contributed only marginally to explaining forest harvesting intensity patterns. Forest harvesting intensity is almost stable along the data range of coniferous tree species cover with predicted values around 60%. This well reflects the approximate average forest harvesting intensity across Europe (see section 1) and high pine and spruce cover goes along with medium to high forest harvesting intensity (e.g., in Central Europe, Scandinavia, and the Baltic countries, Figure II-4b). However, it has to be considered that our differentiation between plantation species and pine and spruce bases on rotation length. Pine and spruce can be interpreted as plantation species as well since they replaced broadleaved forests as Europe's natural forest type due to afforestation practices in the past (Bengtsson et al. 2000). With increasing jobless ratio, a slight increase in predicted forest harvesting intensity was observable with a peak around 10%.

3.4 Variable importance in the time-variant models

We used one-year change ratios and time lags for the time-variant models. Increasing the temporal delay reduced our time series due to data constraints and – when applied – did not improve model results (results not shown). Relative importance of predictor variables and their ranking in the time-variant models were in close agreement to the static model results described in section 3.3 (see also Table SI II-5). Variable rankings were also quite constant over time with an average Kendall *tau* of 0.758 between years (SD = 0.068). Even though the overall model fit did not improve with the consideration of time-variant variables, augmenting the static model with temporal information was essential to investigate effects of socio-economic and natural events on forest harvesting intensity.

Time-lagged forest harvesting intensity (FAOintens*) was significant and fairly stationary over time, likely because transportation networks as well as wood-processing facilities are also relatively static over longer time periods. Hence, forest harvesting intensity in a particular year is a meaningful predictor of forest harvesting intensity in the subsequent year (see Figure II-2). Furthermore, unemployment ratios were important in the beginning of the study period (2000-2002) but showed only marginal influence in the end of the study period (2008-2010). The decrease in relative importance towards the end of the study period could be due to the economic situation deteriorating after the financial crisis in 2008 in many regions.

Most of the variables varied most strongly in and around the year 2006. Static variables dropped in importance whereas some socioeconomic variables drastically gained importance. For example, the influence of the time-lagged forest harvesting intensity peaked in 2006 with a relative contribution of almost 20% (other years: 0.86% to 8.06%) and thus outperforming all other predictors (Table II-3). Furthermore, regional changes in the primary sector labour force were important in 2006 to explain forest harvesting intensity. This is not surprising considering the need for labour to clear the wind throws of the previous year. As stated in section 3.2, the exceptionally low model performance in 2006 (see Table II-2) could be caused by storm Gudrun in 2005 with subsequent salvage logging providing a more than adequate amount of timber, which can be the reason for strongly decreasing forest harvesting intensity in 2006. In fact, 2006 is the only year in our time series, which shows a strong deviation from the general forest harvesting intensity patterns (see Figure SI II-1). Hence, only the time-lagged forest harvesting intensity could – to some degree – capture this exceptional behaviour. However, it has to be considered that other major storm events occurred during or shortly before the study period, such as storms Lothar (1999), Kyrill (2007), or Klaus (2009), which all appear to not have exceptionally influenced forest management schemes and related forest harvesting intensity.

Both, the static and time-variant approach revealed that the four most important spatial determinants of forest harvesting intensity (share of plantation species, country-specific characteristics, terrain ruggedness, and growing stock) also occurred most often as interaction partners (Table SI II-6). Generally, time-variant predictors were only important in certain years, except the jobless ratio and time-lagged forest harvesting intensity. We detected strong interactions between plantation species cover and country-specific characteristics as well as terrain ruggedness.

Table II-3: Relative importance of single predictors for static and time-variant models. Data was missing for GDP PPS*, GVAprim*, and LABOURprim* for 2010. FAOintens* could not be incorporated in the static model since it does not have an average over the study period.

	PREDICTORS	YEAR										
		2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Static
STATIC	PLANTATION	28.87	26.35	16.87	16.51	14.98	13.94	24.28	30.09	38.43	34.96	24.41
	COUNTRY	12.17	14.47	20.54	15.24	20.17	4.40	23.26	11.16	9.29	15.66	13.69
	RUGG	15.91	21.50	19.00	12.61	9.12	14.56	9.06	10.59	9.70	10.04	13.48
	TOTVOL	5.13	5.34	8.34	7.15	5.88	13.93	6.48	8.73	6.69	5.19	9.35
	FCOV	4.31	4.30	5.95	10.42	6.61	13.36	5.10	8.15	4.05	2.65	6.51
	ACC50	4.32	4.43	6.34	7.88	6.53	3.94	4.73	7.74	4.66	5.88	5.31
	PINESPRUCE	5.69	4.71	4.06	4.41	5.22	1.72	6.44	7.33	9.14	7.56	5.20
	TEMP	2.30	1.51	2.27	5.41	4.29	2.93	1.72	2.98	4.39	4.56	3.39
	POORSOIL	2.00	1.59	1.73	1.94	1.41	0.44	2.43	1.49	0.86	1.85	1.77
	PRCP5M	1.32	1.78	1.75	1.87	1.54	0.44	1.12	1.06	1.02	1.61	1.77
	PRIVFOR	2.14	1.28	1.26	1.09	0.83	0.27	0.94	0.81	1.06	1.72	1.54
	WATSHORT	0.91	1.15	1.85	1.56	1.32	0.25	0.62	1.07	0.87	1.63	1.19
	BEECHOAK	0.66	0.64	1.06	1.56	1.97	0.49	0.73	0.87	0.61	1.05	0.96
	TOTPROT	0.85	1.00	1.00	1.07	0.85	0.21	0.52	0.90	0.50	0.61	0.90
	SBC	1.00	0.79	0.67	1.10	1.66	2.91	1.00	0.86	0.57	0.81	0.87
	URBRUR	0.57	0.51	0.59	0.83	0.43	0.15	0.29	0.35	0.40	0.43	0.48
DYNAMIC	FAOintens*	2.86	0.86	2.59	3.96	8.06	18.35	5.72	3.23	4.30	3.58	NA
	JOBLESS*	6.63	4.79	1.27	2.34	2.12	2.34	2.50	0.76	0.84	0.04	4.86
	GDP PPS*	0.75	0.72	0.56	0.49	2.04	0.21	0.83	0.48	0.31	NA	1.59
	GVAprim*	0.58	1.26	0.71	0.88	1.83	0.27	1.06	0.79	1.79	NA	1.41
	LABOURprim*	0.80	0.96	1.54	1.48	1.96	4.83	1.07	0.52	0.45	NA	1.28
	OIL*	0.19	0.05	0.05	0.19	1.16	0.06	0.08	0.04	0.07	0.15	0.05
	TIMBER*	0.05	0.01	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.02	0.00

4 Discussion and conclusion

Although the importance of forest management intensity to address sustained yield has been recognised long ago (von Carlowitz 1713), quantitative, broad-scale assessments of the drivers and spatial patterns of forest management intensity have been missing. Here, we derived forest harvesting intensity patterns as one indicator for forest management intensity for all of Europe using, a system metrics relating the outputs from forestry (i.e., harvests) to ecosystem productivity (i.e., net increment). This allowed us to make forest harvesting intensity comparable across large regions characterized by strong environmental gradients and subsequently to quantify the most important spatial determinants of harvesting intensity at sub-national level. The main conclusions from our analyses and results were:

1. Forest harvesting intensity is distributed unevenly across Europe and harvested timber volumes were mostly well below the increment, thus indicating the potential for sustainable intensification in timber yields.
2. Forest harvesting intensity was well explained by forest-resource related variables (i.e., share of plantation species, growing stock), topography (i.e., terrain ruggedness), and country-specific characteristics.
3. Forest harvesting intensity and some of its predictors exhibit strongly non-linear relationships, sometimes characterised by thresholds. Identifying and understanding such relationships is important for designing and implementing effective sustainable forest management policies.

The spatial patterns of forest harvesting intensity showed marked differences, likely due to regional management practices. The hotspots of high forest harvesting intensity that we identified were mainly within traditional wood producing countries or regions such as Sweden, Finland, or southwest France. By using an intensity measure instead of harvested timber volumes alone, we avoided potential bias in assessing forest harvesting intensity by controlling for differences induced by forest productivity. Our study clearly shows the strong differences that exist between spatial patterns of harvested timber volumes and forest harvesting intensity, emphasizing that assessing timber volume alone may only reveal limited information on management intensity. Despite being a quite simple index, forest harvesting intensity is one of the key indicators to assess sustainable forest management at the European scale. However, to address forest management intensity in an integrated way, further information on harvest frequency, size of production units, tree species selection, harvesting systems, or intensity and frequency of thinning and tending (Schall and Ammer 2013) would have been useful but were not available due to the lack of data.

Generally, we found harvested timber volumes in Europe’s forests to be substantially lower than the net annual increment (Europe-wide approximately 60-65%), resulting in increasing forest growing stocks (Ciais et al. 2008, Forest Europe et al. 2011). Aiming for sustainable use of forest resources, forest harvesting should not get close to or even exceed the annual increment of forests in the long run. Hence, results suggest, that many regions may thus have the capacity for future intensification of timber extraction without compromising the long-term sustainability in terms of wood yield. We caution though that a systemic view and a wide range of indicators should be considered to judge about the overall sustainability of forest management, including the consideration of biodiversity, biogeochemical, and social indicators. Moreover, even intensification at levels well below increment can have strong negative environmental outcomes. Our analyses also highlighted a few regions where harvested timber volumes exceeded the annual increment, which is in line with recent findings of the weakening forest carbon sink strength in Europe, partly because of increasing management intensity (Nabuurs et al. 2013). Harvested timber volumes above the increment can indicate the exploitation of old forests with slower growth rates or a lack of proper management in previous years resulting in short term exceedances. Such trends would, if continued over longer time periods, indicate unsustainable forest use. It is noteworthy to mention that at the national level, harvested timber volumes did not exceed the increment in any of the EU27 countries in 2010 (Forest Europe et al. 2011), whereas our results provide a more nuanced picture pinpointing intensely harvested regions.

Our analyses suggest that the share of plantation species, country-specific characteristics, terrain ruggedness, and growing stock were the most important spatial determinants of forest harvesting intensity. Both regression models we used revealed similar rankings of these predictors hence indicating the stability of our models. Static determinants were generally more important than time-variant ones. A possible explanation for this is that forest harvesting intensity generally depends on long-term environmental and socioeconomic conditions rather than year-to-year changes in such factors given relatively long rotation lengths in forestry. Further reasons could be that much of the information of time-variant socioeconomic variables has been absorbed by country specific characteristics as well as the lower data quality of time-variant predictors. For example, we did not have access to regional-level, annual timber prices and used an approximation using national-level price information on imported and exported roundwood. This is especially unfortunate since timber prices were expected to be an important driver of forest harvesting intensity (Beach et al. 2005). Hence, we assume that the coarse resolution and rough estimation of timber prices may mask their actual importance on forest harvesting intensity.

The identified spatial determinants of forest harvesting intensity differed in several aspects from prior, mainly fine-scale studies investigating the drivers of harvested timber volumes. Prior studies mainly found productivity-related variables to be important (e.g., Beach et al. 2005). An initial analysis revealed that productivity (i.e., net annual increment) was also the most important variable for explaining harvested timber volumes in our study region and model performance of analysing harvested volumes was even higher compared to analysing timber harvesting intensity (results not shown). However, using productivity as a predictor neither allows for assessing forest harvesting intensity, nor for identifying important influential drivers of harvesting which remain masked when not controlling for forest productivity. This again underlines the importance of using intensity metrics that consider system properties to analyse forest harvesting intensity. Comparing our intensity map with the only prior, yet qualitative assessment of forest management intensity on subnational level in Europe (Hengeveld et al. 2012) suggest overall good agreement between these maps. For example, both analyses highlight intensive areas especially in southern Sweden, southern Finland, and southwest France. Whereas the expert-based approach is static, susceptible to personal judgement in the selection of factors, and maps only potential forest management intensity, our approach incorporates time-variant information, identifies the most influential predictors, and addresses forest harvesting intensity explicitly.

A major finding from our study was that the relationship between forest harvesting intensity and predictor variables was sometimes highly non-linear and characterised by threshold-type responses. Such nonlinearity is characteristic for complex socio-ecological systems (Scheffer et al. 2012, Dearing et al. 2010) and emphasise the value of non-parametric statistical approaches. These tools can better uncover and visualise such relationships compared to traditional linear regression models, which have commonly been used. Here, we show that such thresholds may also exist for forestry systems at broad scales (e.g., for plantation species cover and accessibility in our case, Figure II-3). Because non-linearity in socio-ecological systems can result in surprising and sometimes irreversible outcomes, identifying and understanding non-linearity is important for sustainable resource management (Folke 2006).

Our boosted regression tree models explained the variation of forest harvesting intensity well (up to 55% of the with-held variation) and resulted in plausible response curves and robust models without indication of overfitting. The explanatory power of our models was also substantially higher than in previous studies. Nevertheless, a few factors may explain remaining uncertainty. First, data constraints arguably prevented an even higher explanatory power of our models. For example, no data to capture the diversity of decision-making actors (national management plans, NGOs, nature protection organisations, companies, individuals) were available to us, although this should partly be captured by the country dummy. Furthermore, property size, despite being identified as an important determinant of harvesting on the local scale, could not be incorporated because such data are not readily available at the pan-European scale. The distance to wood processing units, such as pulp or saw mills, from harvesting sites likely influences forest harvesting intensity as it affects the procurement costs. Unfortunately, freely available, consistent, complete, and spatially-explicit datasets of processing unit locations are currently not available for all of Europe. It is noteworthy, that our market accessibility variable would likely be highly correlated with a processing unit accessibility variable. Duncker et al. (2012) suggest twelve major factors to characterize forest management intensity, yet not all of these factors could be represented in our dataset (e.g., we had no spatially explicit data on application of fertiliser or pesticides, machinery, or soil cultivation). Furthermore, rapid changes in forest management in response to storm events were only incorporated via our time-lagged forest harvesting intensity, and spatially explicit data on wind throws would have further improved our models. Second, some uncertainty remains due to different national forest harvesting reporting schemes, which may have led to bias in the target variable, even though we controlled for these differences by harmonising the data (see section 2.1). Third, issues of scale cannot be ruled out for regions with a small share of forests, where uncertainty in forest harvesting values may lead to high intensity values (e.g., Northern Italy, see Figure II-1a). Fourth, we used the most recent estimates of industrial roundwood and fuelwood (FAOSTAT 2012) but this may exclude some unrecorded wood removals. Steierer (2010) found that, at the European level, 27 million m^3 or 4% of the total wood supply (forests, outside forests, and industry) was unrecorded. Furthermore, illegal logging activities mainly taking place in Eastern Europe (Knorn et al. 2012, WWF 2007) could not be accounted for in our target variable. Thus, officially available data may underestimate real harvested timber volumes locally and thus forest harvesting intensity. Fifth, the time period we analysed is relatively short compared to average rotation lengths of tree species used for harvesting. Ultimately, we could not quantify uncertainty introduced by the use of different data sets since not all predictors used in this analysis were or even can be validated. We selected the, to our knowledge, best products available that served our thematic (hypothesised influence on forest harvesting intensity) and technical requirements (pan-European coverage, NUTS-level or $1km^2$ spatial resolution). While some of the spatial datasets used in our study were validated (e.g., the forest extent map), statistical data is generally collected and provided without uncertainty estimates.

Fostering more sustainable forest use in light of the growing demands for timber products is a grand challenge and ensuring that future intensification of forest management is sustainable would require considering a range of indicators that address the different facets of forest management intensity. Duly considering the multidimensionality of sustainable forest management appears particularly important considering the potentially non-linear responses we found. Our results have several practical implications for policy makers seeking to balance forest resource use and the conservation of forest ecosystems and biodiversity. First, the bulk of regions in Europe we investigated in this study were characterised by forest harvesting intensities well below the increment, indicating potential for increasing timber yields through intensification. Hence, sustainable intensification may be possible for many regions in Europe in regards to a key indicator: forest harvesting intensity as the ratio of harvested timber to increment volumes. Second, our results suggest that increasing outputs from forestry may be conceivable without altering tree species composition or introduction of new plantation areas, a management practice known to be generally harmful for local biodiversity (Brockerhoff et al. 2008). For example, existing stands could be managed more intensely, especially in Central Europe, although this may lead to increased carbon emissions, biodiversity loss, the reduction of the carbon sink from current forest ecosystems, and degraded forest recreational values due to altered stand naturalness and age structure (Edwards et al. 2010). Third, future policies could focus on extending plantation areas or improving infrastructural accessibility in important timber-producing regions to lower pressure for intensification in other areas. In that way, such analyses can help identifying sustainable solutions by supporting management decisions and landscape architecture (Turner II et al. 2013). Fourth, though the majority of the most important spatial determinants of intensity patterns found in our study were static and cannot easily be changed (e.g., terrain ruggedness, growing stock, forest cover, infrastructure), the two most important determinants we identified provide levers to policy makers and land use planners: plantation species cover and country specific characteristics. Knowing that high forest harvesting intensity relates to high planation share offers action space to modify existing forest management. For example, regions with a large cover of plantation species (especially the Mediterranean countries and western France) could be managed more intensely while considering issues related to biodiversity, environment, and society. Furthermore, a multitude of country specific characteristics, for example forest legislation, policies, or subsidies, promise prospects to influence forest harvesting intensity.

A better understanding of the spatial patterns of forest harvesting intensity and the drivers that produce these patterns are important for understanding the trade-offs between forestry and conservation, and thus ultimately to implement more sustainable forestry systems.

Here, we investigated spatial determinants of continental-scale forestry harvesting intensity patterns. We highlight the potential of such analyses to provide insights beyond traditional studies on harvested timber volumes alone and to identify candidate regions and potential levers to sustainable intensification of forestry. Similar to agricultural systems, the question whether to intensify forest use and conservation in a land sparing approach or to integrate forest use and conservation goals in land sharing landscapes becomes an important question for land use and conservation planners (Tscharntke et al. 2012, Edwards et al. 2014). Clearly, there is no silver bullet to this question, but regional-scale analyses such as ours are an important prerequisite to better understanding where and which strategy could be implemented and what the potential benefits and trade-offs of both strategies are. Our continental-scale study provides a starting point for investigating global forest harvesting intensity. To achieve this, it would be interesting to compare our results with those from studies from other world regions. Finally, our study highlights the value of non-parametric approaches to provide new insights into the determinants of forestry intensity and the usefulness of such analysis to inform forest managers, land use planners, and conservation agencies concerned with the spatial targeting of forest policies or investments.

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Supplementary Information

Table SI II-1: Description of regional harvest data (national data from FAOSTAT was used when no regional data was available).

Country	Spatial detail	Temporal detail	Source
Austria	9 regions (NUTS2)	2002-2010, single years	http://www.forstnet.at/article/archive/27484 [accessed 13.7.2011]
Belgium	3 regions (NUTS1/2)	1998-2007, single years	http://www.fao.org/docrep/013/al456f/al456f.pdf [accessed 13.7.2011]
Bulgaria	16 regions (regional forest directorats)	2000-2010, single years	Data provided by Elena Rafailova and Georgi Kostov
Cyprus	-	-	No regional data available
Czech	14 regions (NUTS3)	2002-2009, single years	http://www.czso.cz/eng/edicniplan.nsf/aktual/ep-1#10 [accessed 13.7.2011]
Denmark	5 regions (NUTS2)	2006-2010, single years	http://www.statbank.dk/statbank5a/default.asp?w=1680 [accessed 19.4.2011]
Estonia	15 regions (NUTS5)	2000-2010, single years	http://pub.stat.ee/px-web.2001/Database/Majandus/11Metsamajandus/11Metsamajandus.asp [accessed 1.12.2011]
Finland	14 regions (forestry centres)	1998-2010, single years	Statistical yearbooks 2000-2010: http://www.metla.fi/metinfo/tilasto/julkaisut/vsk/index.html [accessed 15.7.2011]
France	96 regions (NUTS3)	2000-2010, single years	Data provided by Alexandra Niedzwiedz
Germany	13 regions (NUTS1)	2000-2010, single years	Statistical yearbooks 2006-2010: http://www.destatis.de/jetspeed/portal/cms/Sites/destatis/Internet/DE/Navigation/Publikationen/Querschnittsveroeffentlichungen/JahrbuchDownlads.psml Earlier years: http://www.digizeitschriften.de [accessed 29.8.2011]
Greece	-	-	No regional data available
Hungary	7 regions (NUTS2)	2005-2010, single years	Data provided by Péter Kottek
Ireland	-	-	No regional data available
Italy	107 regions (NUTS3)	2001-2008, single years	http://agri.istat.it/sag_is_pdwout/jsp/Introduzione.jsp?id=7A [accessed 1.4.2011]
Latvia	-	-	No regional data available
Lithuania	-	-	No regional data available
Luxembourg	-	-	No regional data available
Malta	-	-	No regional data available
Netherlands	-	-	No regional data available
Norway	20 regions (NUTS 3)	2000-2010, single years	http://statbank.ssb.no/statistikkbanken/Default_FR.asp?Productid=10.04&PXSid=0&nvl=true&PLanguage=1&tilside=selecttable/MenuSelP.asp&SubjectCode=10 [accessed 12.9.2011]
Poland	16 regions (NUTS2)	2000-2010, single years	http://www.stat.gov.pl/bdlen/app/dane_podgrup.hier?p_id=501574&p_token=-1525468882 [accessed 28.8.2011]
Portugal	-	-	No regional data available

Romania	42 regions (NUTS3)	2000-2010, single years	https://statistici.insse.ro/shop/index.jsp?page=tempo2&lang=en&context=47 [accessed 18.11.2011]
Slovakia	-	-	No regional data available
Slovenia	14 regions (management regions)	2000-2010, single years	Data provided by Anze Japelj
Spain	17 regions (NUTS2)	2003-2005, single years	http://www.ine.es/jaxi/tabla.do [accessed 28.8.2011]
Sweden	21 regions (NUTS3)	1999-2008, 3 year averages	http://www.skogsstyrelsen.se/en/AUTHORITY/Statistics/Subject-Areas/Felling-and-Wood-Measurement/Tables-and-figures/ [accessed 1.4.2011]
Switzerland	26 regions (NUTS3)	2005-2009, single years	http://www.bafu.admin.ch/publikationen/publikation/01578/index.html?lang=de [accessed 29.8.2011]
United Kingdom	4 regions (countries)	2000-2010, single years	http://www.forestry.gov.uk/pdf/Woodproduction1976-2010prov.xls/$FILE/Woodproduction1976-2010prov.xls [accessed 12.9.2011]

Table SI II-2: Description of regional increment data.

Country	**Spatial detail**	**Inventory year**	**Source**
Austria	9 regions (NUTS2)	2000-2002	http://web.bfw.ac.at/i7/oewi.oewi0002 [accessed 30.5.2012]
Belgium	2 regions (NUTS1/2)	1995–1999	EFISCEN database (Verkerk et al. 2011)
Bulgaria	9 regions	2000	Schelhaas et al. 2006
Cyprus	-	-	No regional data available
Czech	-	-	No regional data available
Denmark	5 regions (NUTS2)	2008	http://curis.ku.dk/ws/files/20571766/skov_og_plantager_2008.pdf [accessed 30.5.2012]
Estonia	-	-	No regional data available
Finland	14 regions (forestry centres)	2008	Statistical yearbook 2008: http://www.metla.fi/metinfo/tilasto/julkaisut/vsk/index.html [accessed 15.7.2011]
France	22 regions (NUTS2)		http://www.ifn.fr/spip/ [accessed 21 May 2012]
Germany	13 regions (NUTS1)	2001-2002	http://www.bundeswaldinventur.de [accessed 30.5.2012]
Greece	-	-	No regional data available
Hungary	19 regions (NUTS3)	2006	EFISCEN database (Verkerk et al. 2011)
Ireland	-	-	No regional data available
Italy	21 regions (NUTS2)	2006	http://www.sian.it/inventarioforestale/jsp/documentation.jsp [accessed 30.5.2012]
Latvia	-	-	No regional data available
Lithuania	-	-	No regional data available
Luxembourg	-	-	No regional data available
Malta	-	-	No regional data available
Netherlands	-	-	No regional data available
Norway	7 regions		http://statbank.ssb.no/statistikkbanken/Default_FR.asp?Productid=10.04&PXSid=0&nvl=true&PLanguage=1&tilside=selecttable/MenuSelP.asp&SubjectCode=10 [accessed 21.2.2013]
Poland	-	-	No regional data available
Portugal	-	-	No regional data available
Romania	-	-	No regional data available
Slovakia	-	-	No regional data available
Slovenia	14 management regions	2008	http://www.zgs.gov.si/slo/obmocne-enote/index.html [accessed 30.5.2012]
Spain	17 regions (NUTS2)	1997-2007	http://www.mma.es/portal/secciones/biodiversidad/montes_politica_forestal/estadisticas_forestal/estructura_forestal_2007.htm [accessed 30.5.2012]
Sweden	21 regions (NUTS3)	2004-2008	http://www.skogsstyrelsen.se/en/AUTHORITY/Statistics/Subject-Areas/Forest-and-Forest-Land/Tables-and-Figures/ [accessed 30.5.2012]
Switzerland	25 regions (NUTS3)	2004-2006	http://www.lfi.ch/resultate/regionen-en.php [accessed 22 May 2012]
United Kingdom	4 regions (countries)	1994-2000	Schelhaas et al. 2006

Table SI II-3: Description of regional forest area data.

Country	Inventory year	Source
Austria	2000-2002	http://web.bfw.ac.at/i7/oewi.oewi0002 [accessed 30.5.2012]
Belgium	2000	http://www.fao.org/docrep/013/al456f/al456f.pdf [accessed 13.7.2011]
Bulgaria	2000	Data provided by Elena Rafailova and Georgi Kostov
Cyprus	-	No regional data available
Czech	2004-2008	http://www.uhul.cz/en/il/NIL_AJ.pdf [accessed 30.5.2012]
Denmark	2008	http://curis.ku.dk/ws/files/20571766/skov_og_plantager_2008.pdf [accessed 30.5.2012]
Estonia	2005	http://www.envir.ee/2387 [accessed 1.12.2011]
Finland	2008	Statistical yearbook 2008: http://www.metla.fi/metinfo/tilasto/julkaisut/vsk/index.html [accessed 15.7.2011]
France		http://www.ifn.fr/spip/?rubrique17 [accessed 12.2011]
Germany	2001-2002	http://www.bundeswaldinventur.de [accessed 30.5.2012]
Greece	-	No regional data available
Hungary	2006	EFISCEN database (Verkerk et al. 2011)
Ireland	2005	http://www.agriculture.gov.ie/nfi/nationalforestinventoryresultsdata/ [accessed 30.5.2012] (forest area map only)
Italy	2006	http://www.sian.it/inventarioforestale/jsp/documentation.jsp [accessed 30.5.2012]
Latvia	-	No regional data available
Lithuania	-	http://www.lvmi.lt/vmt/photos/NMI_2008_II%20dalis.pdf [accessed 30.5.2012] (forest area map only)
Luxembourg	-	No regional data available
Malta	-	No regional data available
Netherlands	-	Dirkse et al. (2003)(forest area map only)
Norway	1989	http://www.ssb.no/histstat/nos/nos_c023.pdf [accessed 30.5.2012]
Poland	2000	http://www.stat.gov.pl/bdlen/app / dane_podgrup.hier? p_id = 747948 & p_token = 628195381 [accessed 17.4.2012]
Portugal	-	No regional data available
Romania	2000	https://statistici.insse.ro/shop/index.jsp?page=tempo3&lang=en&ind=AGR301A [accessed 7.2.2012]
Slovakia	-	No regional data available
Slovenia	2008	http://www.zgs.gov.si/slo/obmocne-enote/index.html [accessed 30.5.2012]
Spain	1997-2007	http://www.marm.es/es/biodiversidad/temas/montes-y-politica-forestal/estadisticas-forestales/ [accessed 30.5.2012]
Sweden	2004-2008	http://www.skogsstyrelsen.se/en/AUTHORITY/Statistics/Subject-Areas/Forest-and-Forest-Land/Tables-and-Figures/ [accessed 30.5.2012]
Switzerland	2004-2006	http://www.lfi.ch/resultate/regionen-en.php [accessed 22 May 2012]
United Kingdom	1994-2000	http://www.forestry.gov.uk/website/forstats2010.nsf/LUContents/1C5C0B133710EBC5802573600047FD5A [accessed 30.5.2012]

Table SI II-4: BRT calibration of learning rate (lr) and tree complexity (tc) with the static model. The performance of parameter combinations was checked by 10fold cross-validated correlation coefficients. Bold values indicate best averaged model performance per column and row for tc and lr. The bold value inside the box indicates the final parameter combination of tc and lr used for all models.

		LEARNING RATE									row mean
		0.1	*0.075*	*0.05*	*0.025*	*0.01*	*0.0075*	*0.005*	*0.0025*	*0.001*	
TREE COMPLEXITY	*1*	0.651	0.643	0.642	0.632	0.600	0.625	0.647	0.603	0.625	0.630
	2	0.714	0.713	0.706	0.685	0.730	0.667	0.679	0.698	0.678	0.697
	3	0.699	0.689	0.703	0.683	0.689	0.680	0.713	0.729	0.716	0.700
	4	0.681	0.712	0.689	0.708	0.699	0.719	0.709	**0.724**	0.713	**0.706**
	5	0.678	0.723	0.723	0.684	0.640	0.732	0.684	0.717	0.705	0.698
	6	0.725	0.642	0.725	0.725	0.682	0.698	0.694	0.711	0.653	0.695
	7	0.697	0.704	0.697	0.692	0.732	0.690	0.716	0.689	0.720	0.704
	8	0.641	0.694	0.693	0.695	0.724	0.695	0.711	0.706	0.706	0.696
	9	0.670	0.706	0.689	0.735	0.695	0.762	0.692	0.697	0.663	0.701
col mean		0.684	0.692	0.696	0.693	0.688	0.696	0.694	**0.697**	0.686	0.692

Table SI II-5: Ranking and relative importance of variables included in the analyses. Asterisks indicate time-variant variables, which were averaged for the static model.

Predictor	Relative importance [%]		Predictor ranking	
	static model	mean time-variant model	static model	mean time-variant model
PLANTATION	24.41	24.53	1	1
COUNTRY	13.69	14.64	2	2
RUGG	13.48	13.21	3	3
TOTVOL	9.35	7.29	4	4
FCOV2000	6.51	6.49	5	5
ACC50	5.31	5.65	6	6
PINESPRUCE	5.20	5.63	7	7
FAOintensity*		5.35	---	8
JOBLESS*	4.86	2.36	8	10
TEMP	3.39	3.23	9	9
POORSOIL	1.77	1.57	10	11
PRCP5M	1.77	1.35	11	13
GDP PPS*	1.59	0.71	12	20
PRIVFOR	1.54	1.14	13	14
GVAprim*	1.41	1.02	14	17
LABOURprim*	1.28	1.51	15	12
WATSHORT	1.19	1.12	16	16
BEECHOAK	0.96	0.96	17	18
TOTPROT	0.90	0.75	18	19
SBC	0.87	1.14	19	15
URBRUR_TYPO	0.48	0.46	20	21
OIL*	0.05	0.20	21	22
TIMBER*	0.00	0.01	22	23

Table SI II-6: Interactions of each predictor in the static and the time-variant model. Columns display how many times a predictor was part of an interaction (*Year 2001-2010, Static*), the total count of interactions per predictor in the time-variant models (*Sum*), and the relative occurrence of each predictor as interaction partner in all interactions of the time-variant models (*Ratio*).

	PREDICTORS	**YEAR**												
		01	*02*	*03*	*04*	*05*	*06*	*07*	*08*	*09*	*10*	*Static*	*Sum*	*Ratio*
STATIC	PLANTATION	11	8	8	7	8	8	10	9	12	9	11	90	17.31
	COUNTRY	8	10	11	9	8	4	9	7	8	7	6	81	15.58
	RUGG	5	5	6	7	6	5	4	5	4	2	4	49	9.42
	TOTVOL	4	4	4	4	4	8	7	6	5	3	5	49	9.42
	ACC50	3	4	5	3	4	2	4	5	3	4	3	37	7.12
	TEMP	2	2	2	6	3	2	2	5	4	5	4	33	6.35
	PINESPRUCE	3	4	2	3	3	0	3	6	4	3	4	31	5.96
	FCOV	2	3	3	2	2	4	3	4	3	3	2	29	5.58
	PRCP5M	1	3	2	1	1	0	2	1	2	1	2	14	2.69
	WATSHORT	0	0	1	1	0	0	0	1	2	1	0	6	1.15
	SBC	0	0	0	0	0	4	0	0	1	1	0	6	1.15
	PRIVFOR	2	0	1	0	0	0	1	0	0	0	1	4	0.77
	POORSOIL	1	0	0	0	0	0	1	0	0	0	0	2	0.38
	BEECHOAK	0	0	0	1	0	0	0	1	0	0	0	2	0.38
	URBRUR	0	0	1	0	0	0	0	0	0	0	0	1	0.19
	TOTPROT	0	0	0	0	0	0	0	0	0	0	0	0	0.00
DYNAMIC	JOBLESS*	6	7	1	3	3	4	3	0	1	0	4	28	5.38
	FAOintens*	3	0	1	5	5	6	2	1	1	1	0	25	4.81
	LABOURprim*	0	1	3	0	3	5	0	0	1	0	0	13	2.50
	GVAprim*	0	1	1	0	1	0	0	1	1	0	0	5	0.96
	GDP PPS*	1	0	0	0	0	0	1	0	0	0	2	2	0.38
	OIL*	0	0	0	0	1	0	0	0	0	0	0	1	0.19
	TIMBER*	0	0	0	0	0	0	0	0	0	0	0	0	0.00
	NA	0	0	0	0	0	0	0	0	0	12	4	12	2.31

Figure SI II-1: European administrative units (NUTS0-3) and annual forest harvesting intensity from 2000 – 2010. Maximum felling-to-increment ratios varied between 521% and 769% with the exception of 2006 (1329%).

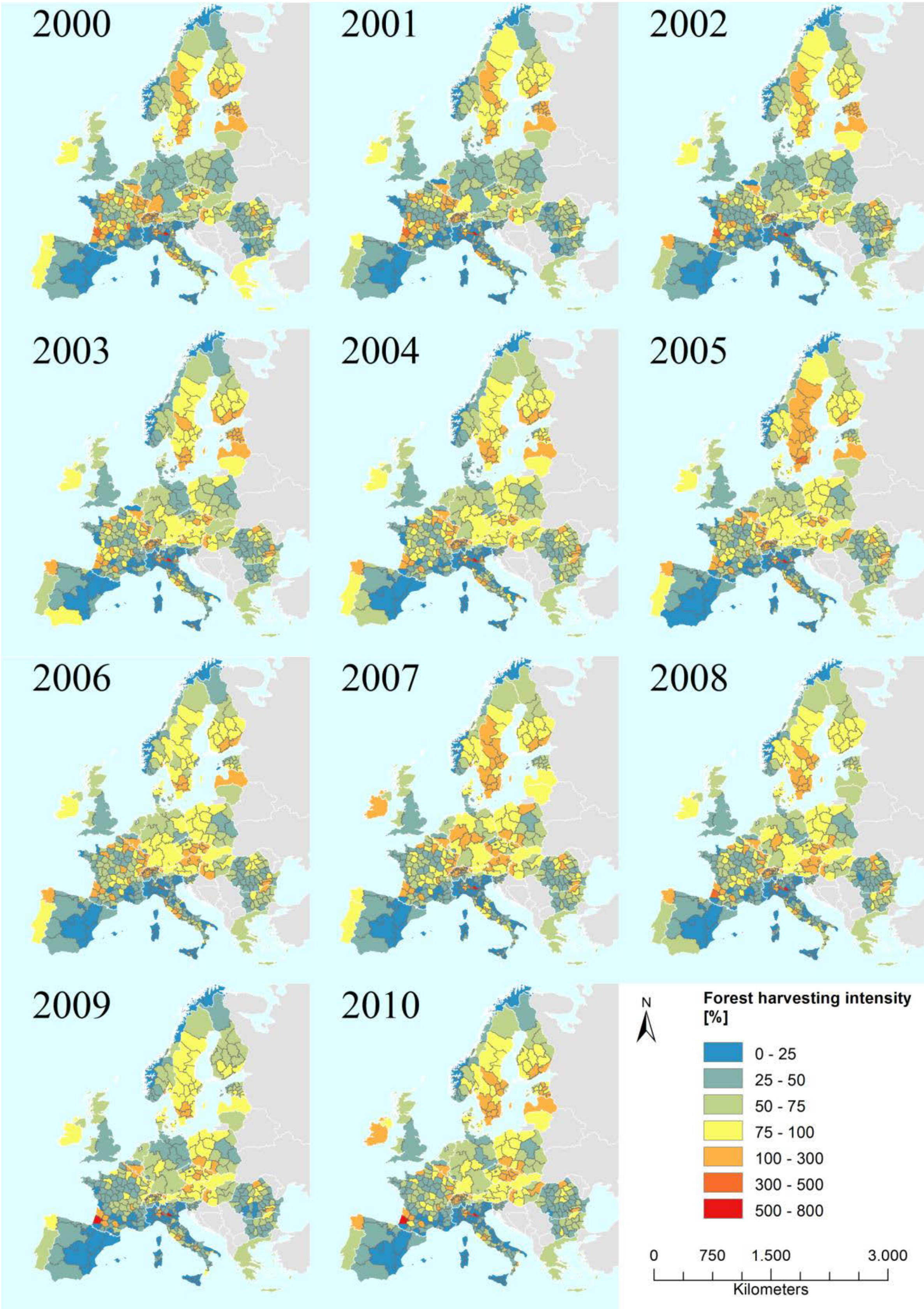
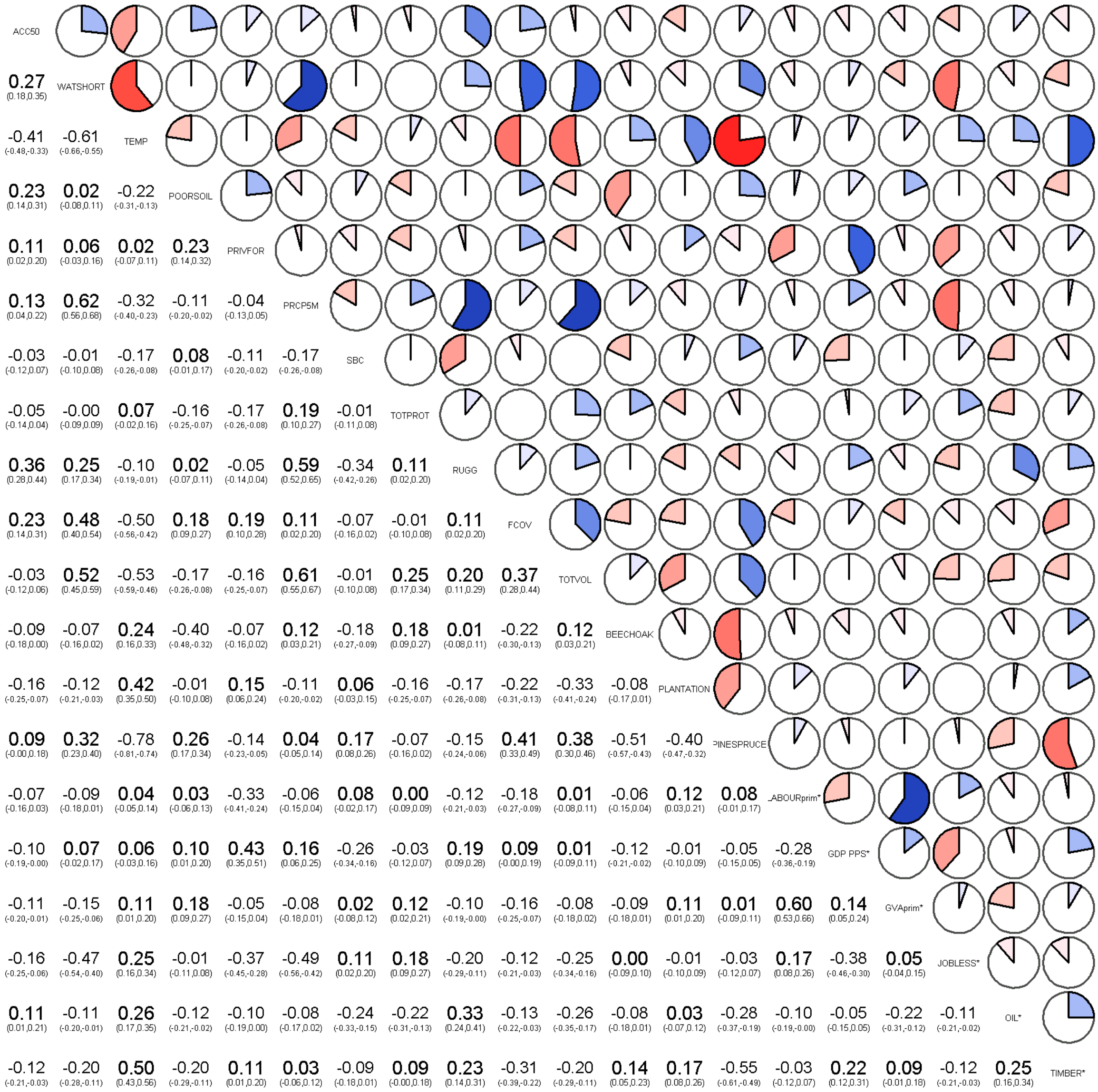


Figure SI II-2: Correlogram of all numeric predictors that entered the model. Upper panel: Red colours indicate a negative relationship, blue colours indicate a positive relationship (for both colours: the darker the colour, the stronger the correlation). Pie charts indicate the magnitude of the correlation, which is also given as correlation coefficients with confidence intervals in the lower panel.



Text SI II-1: Comprehensive description of utilised data.

The following publications were reviewed to extract information of variables potentially influencing forest harvesting intensity: Beach et al. 2005, Bolkesjø et al. 2007, Favada et al. 2009, Størdal et al. 2008, Vokoun et al. 2006, Adams et al. 1991, Arano and Munn 2006, Sterba et al. 2000, and Verkerk et al. 2011.

Regarding forest resource variables, we used six variables (see Table II-1). First, we derived the total growing stock of broadleaved and coniferous tree species (*TOTVOL*) from Gallaun et al. (2010). Second, forest extent and composition may influence harvesting intensity, and we therefore derived the share of forest cover (*FCOV*), and the share of three main tree species groups used for wood production: i) long-rotation broadleaved species consisting of beech (*Fagus spp.*) and oak (*Quercus robur, Quercus petraea*) (*BEECHOAK*), ii) long-rotation coniferous species consisting of spruce (*Picea spp.*) and Scots pine (*Pinus sylvestris*) (*PINESPRUCE*), and iii) short-rotation and plantation species consisting (e.g., *Pinus pinaster, Robinia spp., Populus spp.,* and *Eucalyptus spp.*) (*PLANTATION*). Finally, we also calculated the share of protected forest areas by combining all IUCN protection categories (IUCN and UNEP-WCMC 2012), since they may restrict harvesting activities (*TOTPROT*).

We derived six variables describing environmental conditions (see Table II-1). We used the share of forest area on low productive soils (Histosol, Ranker, Arenosol, Lithosol, Xerosol, Solonchak, Regosol, Acrisol, Solonetz, Marsh) (*POORSOIL*), precipitation during the growing season (March to July) (*PRCP5M),* and mean annual temperature (*TEMP*) to approximate growth limitations (Yang et al. 2006). Soil data was obtained from the European Soil Data Base (EC 2006b), information on temperature and precipitation was derived from Hijmans et al. (2005). We also calculated the difference between precipitation and potential evapotranspiration during the growing season (*WATSHORT*) to account for water stress. We calculated terrain ruggedness (*RUGG*), which expresses the amount of elevation difference between adjacent cells of a digital elevation grid, following Riley et al. (1999). Ruggedness calculations were based on elevation data from the Shuttle Radar Topography Mission (NASA 2006) dataset, because very rugged terrain is less accessible for harvesting. Finally, we calculated the share of forest on soil with none or limited bearing capacity (Histosol, Fluvisol, Gleysol, Andosol) (*SBC*), because wet soils can prevent the use of machinery (Verkerk et al. 2011).

As for socio-economic variables, eleven variables were derived. First, we used the travel time of a location to settlements larger 50,000 inhabitants (*ACC50*) calculated by Nelson (2008) because market access and infrastructural networks can strongly determine land use changes, for example deforestation (Geist and Lambin 2002). Economic incentives and restrictions, subsidies, market prices, or interest rates can all influence harvesting activities, but spatially explicit data at the sub-national scale is often very scarce. We approximated roundwood timber prices by summing up import and export prices obtained from FAOSTAT (2012) and dividing it by the sum of import and export volumes of roundwood as done in Solberg (2011) (*TIMBER**). Furthermore, we assumed higher harvesting intensity in times of high energy prices, when wood may substitute oil-based energy supply. To proxy energy prices, we used heating oil prices including tax from the European Commission (EC 2013b) (*OIL**). For this variable, information was not available before the year 2000. We extrapolated these values based on price reports without taxes of the year 2000 to be able to calculate change ratios for our study period. Gross domestic product per inhabitant in purchasing power standard (*GDP PPS**), unemployment ratio (*JOBLESS**) and gross value added (*GVAprim**) as well as the labour force of the primary sector (*LABOURprim**) were used as indicators of economic activity. We approximated ownership related harvesting schemes by calculating the share of privately owned forest (*PRIVFOR*). Finally, we included the urban-rural typology (*URBRUR*; EEA 2010) to account for differences induced by rurality among regions and used a country dummy variable (COUNTRY) to capture all country-specific characteristics and events (socioeconomic and environmental) that could not be implemented in the model otherwise (due to the lack of spatially explicit data on these characteristics). Such characteristics may include lifestyle, policies, management legacies, or fire and storm events. The country dummy was created as a categorical variable by numerating all countries according to the latitude of their centroid (islands removed).

Chapter III:
Mapping wood production in European forests

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Abstract

Wood production is an important forest use, impacting a range of other ecosystem services. However, information on the spatial patterns in wood production is limited and often available only for larger administrative units. In this study, we developed high-resolution wood production maps for European forests. We collected wood production statistics for 29 European countries from 2000 to 2010, as well as comprehensive sets of biophysical and socioeconomic location factors. We used regression analyses to produce maps indicating the harvest likelihood on a 1×1 km^2 grid. These likelihood maps were validated using national forest inventory plot data. We then disaggregated wood production statistics from larger administrative units to the grid level using the harvest likelihood as weights. We verified the resulting wood production maps by correlating predicted and observed wood production at the level of smaller administrative units not used for generating the wood production maps. We conclude that (i) productivity, tree species composition, and terrain ruggedness are the most important location factors that determine the spatial patterns of wood production at the pan-European scale and that (ii) incorporating these location factors substantially improves the results of disaggregating wood production statistics compared to a disaggregation based on forest cover only. Our wood production maps give insight into forest ecosystem service provisioning and can be used to improve the assessment of potentials and costs of woody biomass supply.

1 Introduction

Forests provide a broad range of ecosystem services that are important to human society (MA 2005a). Wood production represents a key provisioning service and global wood production amounted to 3.4 billion m^3 in the year 2005 (FAO 2010). Because wood production affects the provisioning of other services and biodiversity (Schwenk et al. 2012; Verkerk et al. 2014a, Zanchi et al. 2014), spatially explicit information on wood production is important for the design and implementation of policies targeted at sustainable forest use (cf. Cowling et al. 2008, Maes et al. 2012).

Statistical information on wood production can be combined with land-cover maps (i.e., forest cover maps) to develop wood production maps (Maes et al. 2012). Yet, the use of forest cover as the only proxy to map wood production is a coarse and simplistic approach that may result in substantial errors (Eigenbrod et al. 2010), because production patterns may not be equally distributed across forested landscapes (Wendland et al. 2011, Masek et al. 2011). This suggests that determinants other than forest cover should be considered when mapping wood production patterns.

A few studies have recently attempted to map wood production or forest management in general. For example, Hurtt et al. (2006) mapped wood production at a global level, assuming that forest cover and proximity to transportation infrastructure determined the spatial patterns of production. Within Europe, Hengeveld et al. (2012) mapped different forest management alternatives and identified areas with intensive forest management focusing on wood production, as well as areas with management objectives other than wood production. Furthermore, Levers et al. (2014) mapped harvesting intensity across European forests (i.e., wood production in relation to the net annual increment) and assessed the drivers of harvesting intensity at the level of administrative units. They found that harvesting intensity is driven by a combination of forest-resource related factors (i.e., the share of plantation species, growing stock, forest cover), site conditions (i.e., topography, accessibility), and country-specific characteristics. However, their analysis focussed primarily on understanding drivers of harvesting intensity and was restricted to exploring spatial patterns for larger administrative units (national to provincial level or forestry districts) thereby not addressing wood production at the grid level.

Existing studies suggest that knowledge of the factors driving patterns in wood production can improve the disaggregation of wood production statistics substantially. In such an approach first a statistical relationship between a target variable (e.g., wood production) and its location factors (e.g., soil quality, topography, accessibility) is established at the level of the aggregated target data (e.g., for administrative units). Second, this relationship is then used to predict the suitability of every location for the target variable at the target grid level for which information on the location factors are available. Such a downscaling approach in which statistical relationships are transferred across scales is called dasymetric mapping (Eicher and Brewer 2001) and has been used extensively to disaggregate national- or regional-level land-use extent (Dendoncker et al. 2007), farming systems (van de Steeg et al. 2010), livestock (FAO 2007, Neumann et al. 2009), or nitrogen input (Temme and Verburg 2011). In a forestry context, dasymetric mapping was used to derive gridded maps of tree species presence for Europe (Brus et al. 2012) and at the global scale to map growing stock, forest biomass (Kindermann et al. 2008) and wood production (Hurtt et al. 2006). The latter maps have been generated at a resolution of 1° × 1° grid cells, using coarse, national-scale data on wood production, mainly targeted as an input for global climate and vegetation models. These applications strongly highlight the potential for dasymetric mapping to provide insights into wood production patterns, but a fine-scale application of this kind is missing for Europe, and as a result the spatial patterns of wood production remain weakly understood.

Here, we present an approach to fill this knowledge gap by developing high-resolution wood production maps for European forests (in this study limited to 27 European Union member states, plus Norway and Switzerland) for the period 2000-2010 at a resolution of 1×1 km^2 grid cells. Our objectives were (i) to analyse the location factors determining wood production patterns in Europe, (ii) to assess whether information about the relationship between wood production and location factors improves the disaggregation of wood production statistics, and (iii) to derive time series of wood production maps for Europe.

2 Material and methods

2.1 Data

Wood production data

We collected data on wood production from national forestry reports, statistical yearbooks and databases, and by contacting national experts known to the authors (Table SI II-1 in the

Supplementary Information) for the years 2000 to 2010 for 460 administrative units within the 29 countries in our study. The number of administrative units per country varied from 1 (national level) to 107 (provincial or forestry district level). The statistics that were collected followed national definitions and differed in e.g. whether wood production volumes were reported as over or under bark, or included harvest losses. To account for these differences, we harmonised the wood production data by calculating the share of harvested wood volume for each administrative unit relatively to the national total wood production. These shares were calculated as averages for all years for which regional data was available in our dataset. Shares were then multiplied with national-level harvest data. For the latter, we used annual roundwood production (m^3 under bark) statistics from FAOSTAT (2012), because these data are reported following harmonised definitions and data were available for each year in our study period. To use the data for statistical analyses, we divided harvest volume by forest area in each region (Table SI II-3 in the Supplementary Information). To mitigate problems due to differences in national definitions, we calculated the area share of each unit in the total forest in a particular country and multiplied it with the forest area in 2000 according to Forest Europe et al. (2011). The outcome was a set of maps of harmonised wood production statistics [WOOD; m^3 ha^{-1} yr^{-1}] at the level of administrative units.

Location factors

We reviewed literature to identify potential location factors that could affect the likelihood of harvesting at a given location. The literature review focussed on understanding the harvesting behaviour of forest owners (Beach et al. 2005, Bolkesjø et al. 2007, Butler 2006, Favada et al. 2009, Størdal et al. 2008, Vokoun et al. 2006, Adams et al. 1991, Arano and Munn 2006), as well as on wood supply in more general terms (Sterba et al. 2000, Verkerk et al. 2011). Based on our review and data availability for the entire study area, 16 potential location factors influencing the likelihood of harvest were identified, as well as a priori assumptions with regards to the direction of influence of each location factor on harvesting likelihood (Table III-1). This set of potential location factors is similar to the set used by Levers et al. (2014). A key difference is that we used net annual increment as an additional predictor, as it may strongly influence the location of wood production, whereas Levers et al. (2014) used net annual increment to normalise harvest in order to obtain a more direct indicator of harvesting intensity at the level of administrative units.

Table III-1: Description of location factors used in the regression analyses.

Predictor	Abbreviation	Description	Expected impact	Unit	Source
		Forest resources			
Extent of forest	*FCOV2000*	Forest cover in 2000	+	%	Pekkarinen et al. 2009
Growing stock	*TOTVOL*	Total growing stock	+	m^3 ha^{-1}	Gallaun et al. 2010
Productivity	*NAI*	Net annual increment (average over 2000-2010)	+	m^3 ha^{-1} yr^{-1}	See Table SI II-2 in the Supplementary Information
Tree species composition	*BEECHOAK*	Share of beech (Fagus spp.) and oak (Quercus spp.) in total species	+	%	Brus et al. 2012
	PINESPRUCE	Share of Scots pine (Pinus sylvestris) and spruce (Picea spp.) in total species	+	%	Brus et al. 2012
	PLANTATION	Share of plantation species (Robinia spp., Populus spp., Eucalyptus spp., Pinus pinaster) in total species	+	%	Brus et al. 2012
Protected areas	*TOTPROT*	Share of protected forest in total forest	-	%	IUCN and UNEP-WCMC 2012; EEA 2011
		Environmental conditions			
Soil productivity	*POORSOIL*	Share of low productive soil limiting growth	-	%	Verkerk et al. 2011
Precipitation	*PRCP5M*	Precipitation sums of growing season	+/-	mm	Hijmans et al. 2005
Temperature	*TEMP*	Long term mean temperature	+/-	°C	Hijmans et al. 2005
Water shortage	*WATSHORT*	Difference between precipitation and potential evapotranspiration	-	mm	Hijmans et al. 2005
		Accessibility			
Accessibility	*ACC50*	Travel time to cities > 50,000 inhabitants	+	min	Nelson 2008
Slope	*RUGG*	Terrain ruggedness expressing relief energy	-	m	Riley et al. 1999; C. Plutzar, pers. comm.
Soil bearing capacity	*SBC*	Share of soil types with no bearing capacity	-	%	EC 2006b, Verkerk et al. 2011
		Socio-economy			
Private forests	*PRIVFOR*	Share of forest that is privately owned	+/-	%	Pulla et al. 2013
Population density	*POPDENS*	Population density (number of people per square kilometre)	-	pers/ km²	Oak Ridge National Laboratory 2004

Most data on location factors were available as raster maps with a resolution of 1 × 1 km^2 grid cells. Where data were available at a finer resolution, we aggregated them using bilinear interpolation based on the weighted distance of the four nearest input cell centres.

Data layers that were available for administrative units were rasterized to the 1 × 1 km^2 grid assuming homogeneity across administrative units. Maps of the location factors are shown in Figure SI III-1 in the Supplementary Information. Details on the data pre-processing of the predictor variables are provided in the Supplementary Information of Levers et al. (2014) (cf. Chapter II).

To match the spatial resolution of our location factors to that of the wood production statistics, we calculated average values of our location factors for each of the administrative units for which we had collected wood production statistics. In case location factors were not limited to forests (e.g., POORSOIL in Table III-1), we weighted location factor values according to forest cover for each administrative unit. To do so, we multiplied relevant location factor maps with a fractional forest cover map. We used the forest map by Pekkarinen et al. (2009), which was calibrated following an approach by Päivinen et al. (2001) to match regional-and national-level forest area statistics (Table SI II-3 in the Supplementary Information). As a result, the values of location factors at locations with higher forest cover had a larger share in the average predictor value at the administrative unit level, compared to pixels with little forest cover.

We also investigated possible collinearity between location factors, but did not find correlation coefficients exceeded 0.7 (Figure SI III-2 in the Supplementary Information) and therefore considered all location factors for subsequent regression analyses.

2.2 Regression analysis

To analyse how our set of location factors influences the spatial patterns of wood production, we employed two regression techniques: (i) a model selection using traditional, linear regression modelling combined with Bayesian Model Averaging (BMA) and (ii) Boosted Regression Trees (BRTs). Algorithmic regression models such as BRTs often outperform traditional, linear regressions in terms of predictive accuracy while being able to model non-linear, complex relationship and being less affected by small sample size and collinearity in input data. However, such non-linear, complex models might be disadvantageous in dasymetric mapping, because they may result in over- or underestimation when transferring models from the level of administrative units to the grid level. Traditional linear regressions, while potentially less powerful in terms of predictive power, yield regression coefficients that are more robust to scaling between the level of model fitting and prediction (Easterling 1997, Jelinski and Wu 1996). Hence, we decided to compare both approaches. For all analyses we used WOOD averaged over our entire study period as the dependent variable, and the location factors as independent variables. We used R (R Core Team 2014) for all statistical analyses, including the packages *dismo* (Hijmans et al. 2013; Boosted Regression Trees), *BMA* (Raftery et al. 2013; Bayesian model averaging), and *raster* (Hijmans et al. 2014).

Bayesian Model Averaging

Our first model (hereafter referred to as linear model) was obtained using BMA. We applied BMA to account for uncertainty in the process of model selection, which may lead to over-confident inferences (Hoeting et al. 1999). A single-best model is usually selected among alternative models based on hypothesis tests and goodness-of-fit measures (Raftery et al. 1997). Alternative models that may perform equally well as the “best” model are thus neglected (Hoeting et al. 1999). BMA provides a solution to this by averaging over all possible models to derive a model that accounts for uncertainty in the model selection process and usually yields a better predictive performance compared to a single-best model (Raftery et al. 1997, Madigan and Raftery 1994).

To carry out the BMA, we used the *bicreg* function of the BMA package that uses the Bayesian Information Criterion (BIC; Hastie et al. 2011) to identify the 25 best models of all possible models. We then used the five best candidate models to select the final suite of location factors for the linear model following Raftery et al. (2005). We included only location factors which were consistently selected throughout all 25 best models. We furthermore calculated the cumulative posterior probability of the five best candidate models to estimate the probability that the “true” model consists of their suite of location factors.

Boosted Regression Trees

Boosted Regression Trees are a machine learning technique that combines high predictive accuracy with a good interpretability of results (Friedman 2001). BRTs are robust against overfitting (Dormann et al. 2013), missing data, and collinearity of location factors, while being able to handle non-linear relationships and variable interactions well (Elith et al. 2008). We fitted two models using BRTs; one with the location factors identified by BMA for the linear model (hereafter referred to as BRT1 model) and another using the full suite of location factors (hereafter referred to as BRT2 model). We developed these two models to improve the comparability of results since BRTs selected different variables as most influential in comparison to BMA due to differences in model characteristics.

To parameterise BRTs, four main parameters have to be specified: (i) regression tree complexity, (ii) learning rate, (iii) number of regression trees, and (iv) bag fraction. Tree complexity defines the allowed number of interactions in the model and learning rate defines the contribution of each single decision tree to the entire model. The number of trees defines how many single decision trees are used in the model. Finally, the bag fraction defines the amount of data (i.e., observations) that is withheld while fitting individual tree models. We performed an optimisation routine to determine the optimal settings for tree complexity and learning rate. We tested interaction levels from 1 to 9 and learning rates from 0.1 to 0.001 and identified the optimal parameter combination using 10-fold cross-validated correlation coefficients. Finally, we set tree complexity to 8 for the BRT1 model (same location factors as in the BMA) and 6 for BRT2 model (all location factors) as well as learning rate to 0.005 and bag fraction to 0.5 for both BRT models.

We employed the *gbm.step* routine provided by the *dismo* package to determine the optimal number of trees. To evaluate model performance, we used a 10-fold cross-validation to calculate Pearson's correlation coefficient and the percentage of deviance explained (Elith et al. 2008). For interpreting results of both BRT models, we regarded only those variables as influential which relative importance exceeded that expected by chance (100%/number of variables; i.e. 100%/16 = 6.25%) (Müller et al. 2013). The relative importance thus depends on how often a variable is selected in the models' regression trees and the weighted improvement to the model (Friedman and Meulman 2003). The sum of all variables' relative importance adds up to 100%, with higher values indicating a stronger influence of this particular variable on the target variable (i.e., wood production in our case). To investigate the relationship between each predictor and the target variable, we used partial dependency plots (PDPs) that depict response curves for each location factor along its data range in relation to the wood production while holding all other location factors at their mean (Friedman 2001).

2.3 Disaggregation and accuracy assessment

To produce wood production maps, we followed the procedure illustrated in Figure III-1. We first applied the above regression models to produce harvest likelihood maps, and we then used these likelihood maps as a basis to disaggregate wood production statistics to the grid level. We developed one likelihood map for each of the three final regression models (linear, BRT1, and BRT2, i.e. three harvest likelihood maps in total) by predicting wood

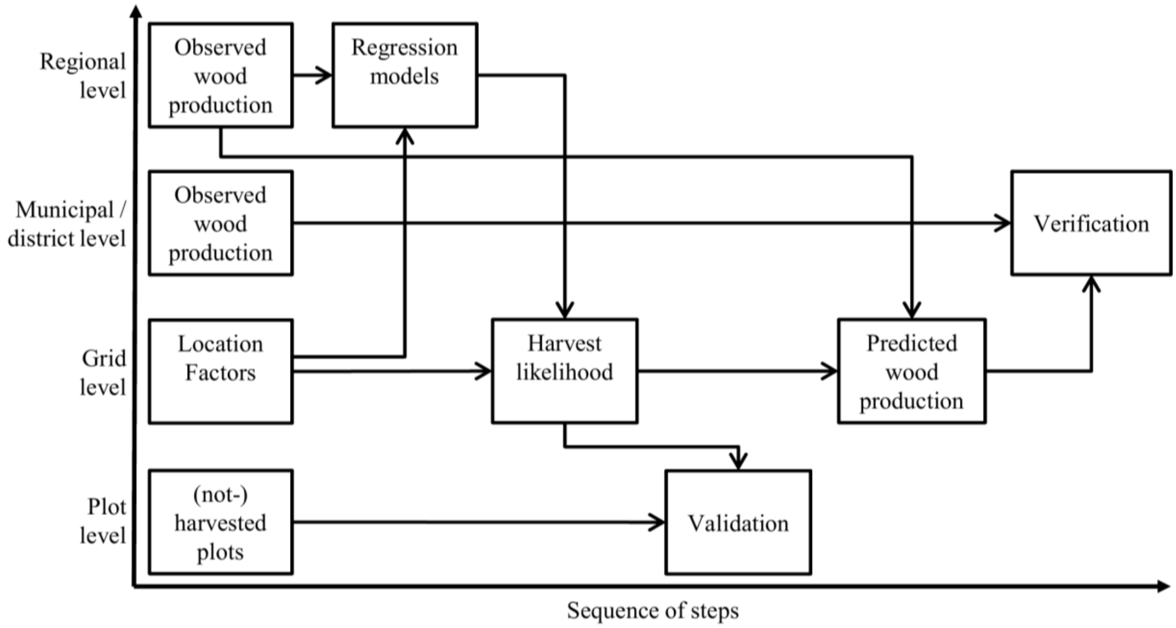


Figure III-1: Flowchart describing the steps to develop wood production maps for European forests at a resolution of 1 × 1 km^2 grid cells.

production at the 1 × 1 km^2 grid level and normalising the predictions to values between 0 (low likelihood) and 1 (high likelihood) using the minimum and maximum values.

We then validated the three likelihood maps using plot data from the 3rd Spanish National Forest Inventory (MAGRAMA 2013). We used data from a total of 84,264 plots that were located on the Spanish mainland and had a forest cover >20%, of which 224 plots (0.27%) were classified as being recently harvested. We determined the harvest likelihood value for each of the inventory plots of the linear and the two BRT models. We hypothesised that the recently harvested plots had a larger likelihood score than the unharvested plots and we tested for significance with one-tailed Mann-Whitney U tests, as data were not normally distributed in all cases.

After generating and validating the harvest likelihood maps, we developed a disaggregation procedure to map wood production at the grid level. To test whether the disaggregation of wood production statistics is improved by adding information on location factors of wood production patterns, we first disaggregated wood production volumes based on forest cover only. The wood production volume that was allocated to an individual pixel was based on the forest cover of that pixel proportional to the total forest area of all pixels in this administrative unit. Subsequently, we relied on the same disaggregation procedure, but included information from the likelihood maps. We did this by multiplying each harvest likelihood map with the forest cover map. As a result, the wood production volume that was allocated to an individual pixel was larger for pixels with higher harvest likelihood and higher forest cover values, compared to pixels with e.g. higher harvest likelihood, but lower forest cover values.

We verified our disaggregation results following Neumann et al. (2009) and re-aggregated grid-level wood production to the level of finer administrative units than those used for building the regression models and for which independent data was available. We verified our disaggregation results for 44 districts in Baden-Württemberg (Germany) and for 410 municipalities in Norway. We used Spearman correlation tests to test how well our predictions matched with observed wood production levels. To avoid inflating correlation coefficients, we excluded countries for which we had only data at the national level. Furthermore, we calculated difference maps between predicted wood production (based on the disaggregation of national level statistics) and observed wood production at the level of administrative units. Based on this accuracy assessment, we selected the likelihood map that resembled observed wood production statistics best and produced a final European-wide wood production map. We used R (R Core Team 2014) for all statistical analyses, including the *rgdal* (Bivand et al. 2014) and *raster* (Hijmans et al. 2014) packages.

3 Results

3.1 Regression results

The cumulative posterior probability of the top five BMA models was 0.79, indicating a high probability that the “true” model consists of location factors selected by these models. Six location factors were selected based on their posterior probabilities of inclusion: POORSOIL, PRCP5M, RUGG, PLANTATION, PINESPRUCE and NAI. These variables were consistently selected in each of the top five models. We used these six location factors in the final linear model with wood production averaged over the entire 11-year period as the dependent variable (WOOD). The final linear model was expressed as follows:

$$WOOD = a + bPOORSOIL + cPRCP5M + dRUGG + ePLANTATION + fPINESPRUCE + gNAI$$

in which coefficients *a-g* are the regression parameters. The results of the regression

Table III-2: Results of the linear model. The abbreviations of the location factors are explained in Table III-1. Significance levels: * p<0.01; ** p<0.001.

Coefficient		*Estimate*	*SE*
a	*Intercept*	-1.181*	0.369
b	*POORSOIL*	-0.021**	0.006
c	*PRCP5M*	0.006**	0.001
d	*RUGG*	-0.013**	0.002
e	*PLANTATION*	0.056**	0.010
f	*PINESPRUCE*	0.021**	0.004
g	*NAI*	0.331**	0.047

analysis for the linear model are presented in Table III-2. The linear model was highly significant ($p<0.005$) and explained (adjusted R^2) about 45% of the variance in wood production patterns. All location factors confirmed our a priori assumptions with regards to the direction of their influence (positive or negative; see also Table III-1) on wood production. NAI revealed the strongest absolute effect on wood production.

The same set of six location factors was used in the BRT1 model (Figure III-2) and explained about 67% of the variance in wood production patterns. Similar to the linear model, NAI was the most important variable for explaining the spatial patterns in wood production with a relative importance of about 30%, whereas PLANTATION was the second-most important predictor with a relative importance of about 26%. All location factors had the same, expected sign as for the linear model. However, the boosted regression trees revealed that not all location factors were linearly related to wood production at the administrative level. In case of PLANTATION, for example, wood production was found to decrease below a threshold of 20% plantation species in total forest cover, after which it increased and saturated at a threshold of 40% plantation species.

The BRT2 model (Figure III-3) performed slightly better than the BRT1 model, explaining about 71% of the variance in wood production patterns. The location factors NAI, PLANTATION, RUGG, ACC50, and TOTVOL were most influential. Similar to the other models, NAI was the most important variable (24%) for explaining the spatial patterns in wood production and PLANTATION (18%) was the second-most important predictor. Compared to the other models, POORSOIL, PRCP5M were less important in the BRT2 model. Instead, ACC50, RUGG and TOTVOL were found to be influential. Similar to the BRT1 model, the BRT2 model revealed that not all location factors were linearly related to wood production at the level of administrative units.

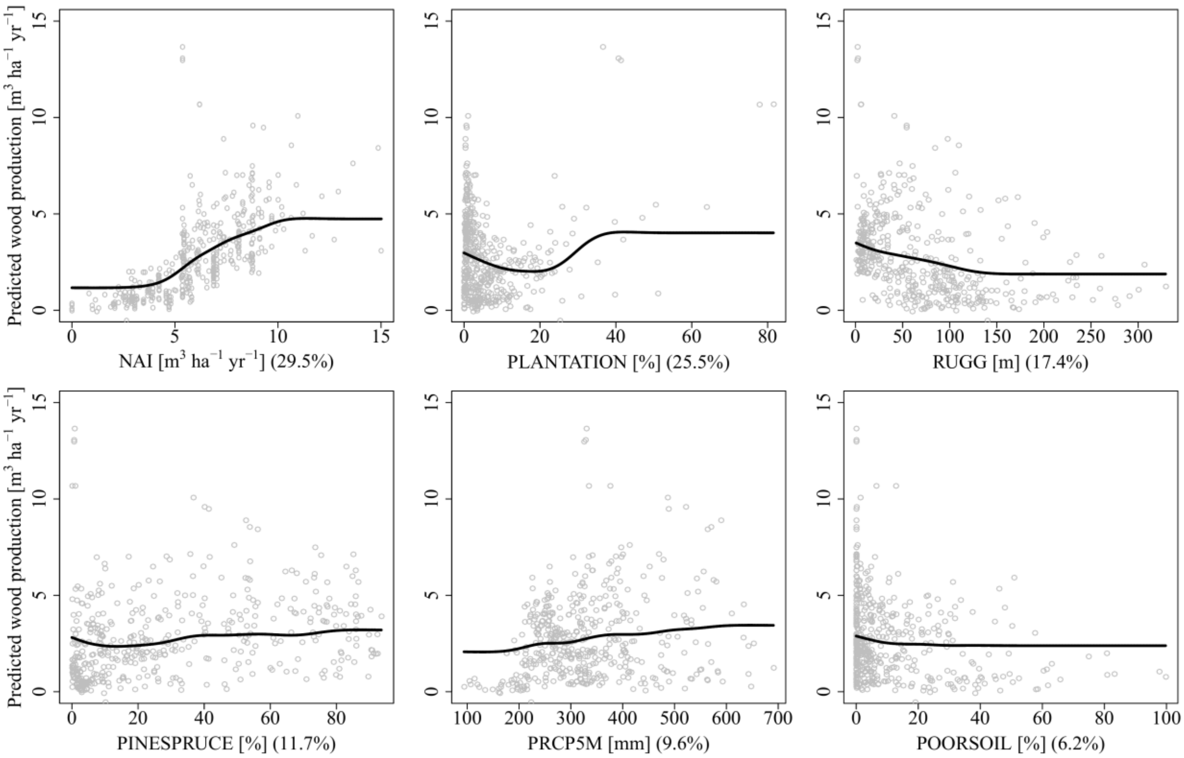


Figure III-2: Partial dependency plots for the BRT1 model using six location factors selected by Bayesian model averaging. The y-axis [unit: m^3 ha^{-1} yr^{-1}] of each plot shows the fitted values for each observation along the variable's data range displayed on the x-axis. The ticks on the x-axis visualise the distribution of the data in deciles. The unit of each predictor is described in Table III-1.

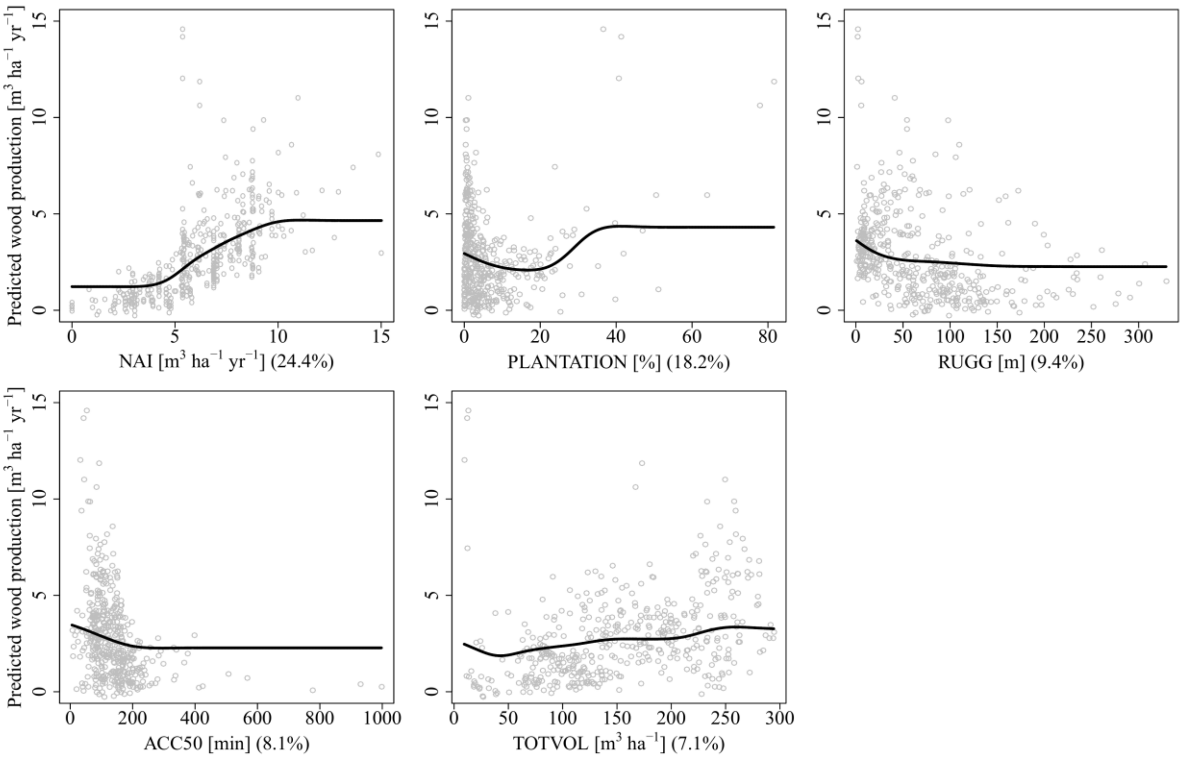


Figure III-3: Partial dependency plots for the BRT2 model. The y-axis [unit: m^3 ha^{-1} yr^{-1}] of each plot shows the fitted values for each observation along the variable's data range displayed on the x-axis. The ticks on the x-axis visualise the distribution of the data in deciles. The unit of each predictor is described in Table III-1.

3.2 Accuracy assessment

We applied the regression models to produce three harvest likelihood maps, one for each regression model (Figure SI III-3 in the Supplementary Information). Utilising the Spanish forest inventory plot data, we tested whether recently harvested plots had a larger harvest likelihood score compared to unharvested plots. The results of three one-tailed Mann-Whitney U tests showed that recently harvested plots had significantly ($p<0.005$) higher likelihood scores as compared to unharvested plots for all three likelihood maps (Table III-3).

Table III-3: Median likelihood score of three likelihood maps for harvested (n=224) and unharvested (n=84040) Spanish forest inventory plots and the significance levels according to one-tailed Mann-Whitney U tests.

Coverage	Harvested	Unharvested	p-value
Linear model	0.38	0.20	<0.001
BRT1 model	0.23	0.09	<0.001
BRT2 model	0.21	0.09	<0.001

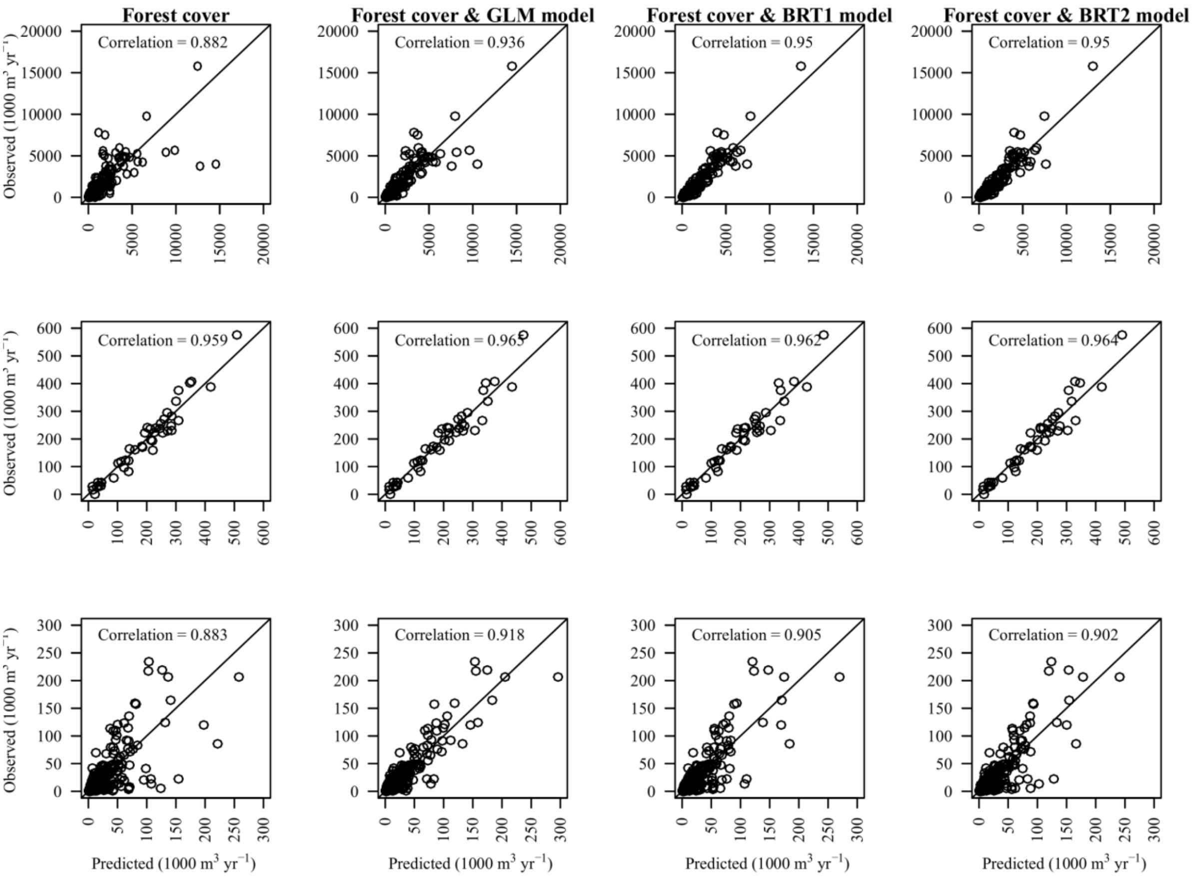


Figure III-4: Results of Spearman correlation tests between observed and predicted total wood production [unit: 1000 m^3 yr^{-1}]. Tests were based on disaggregating statistics using four different likelihood maps for Europe (from 19 countries to 451 administrative units; top row), Baden-Württemberg (from 1 state to 44 districts; middle row) and Norway (from 19 provinces to 410 municipalities, bottom row).

Using the forest cover map, as well as the three harvest likelihood map, we disaggregated wood production statistics to the grid level. To verify the resulting wood production maps we re-aggregated from the grid-level to the level of finer administrative units and compared the predicted wood production with observed data at the level of administrative units using fine-scale harvesting statistics for Europe, Baden-Wuerttemberg and Norway. Results of Spearman correlation tests (Figure III-4 and Figure III-5) between predicted and observed wood production revealed that disaggregating based on forest cover solely yielded the poorest results. When considering additional information (compared to forest cover only), the correlation between predicted and observed wood production improved substantially. Between the three regression-based likelihood maps, we observed only minor differences. The disaggregation based on the linear model showed slightly higher correlations compared to the disaggregations based on the two BRT models.

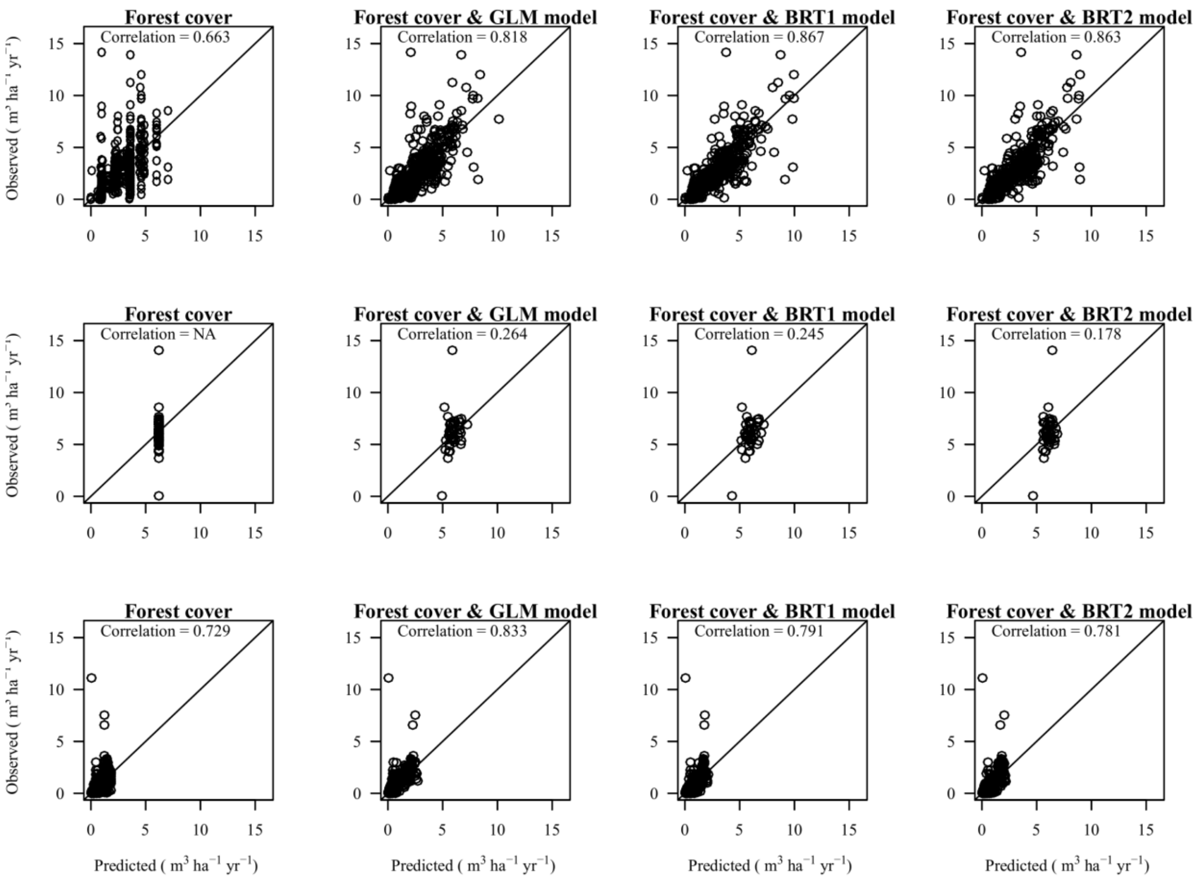


Figure III-5: Results of Spearman correlation tests between observed and predicted wood production per unit of forest area [unit: m^3 ha^{-1} yr^{-1}]. Tests were based on disaggregating statistics using four different likelihood maps for Europe (from 19 countries to 451 administrative units; top row), Baden-Württemberg (from 1 state to 44 districts; middle row) and Norway (from 19 provinces to 410 municipalities; bottom row).

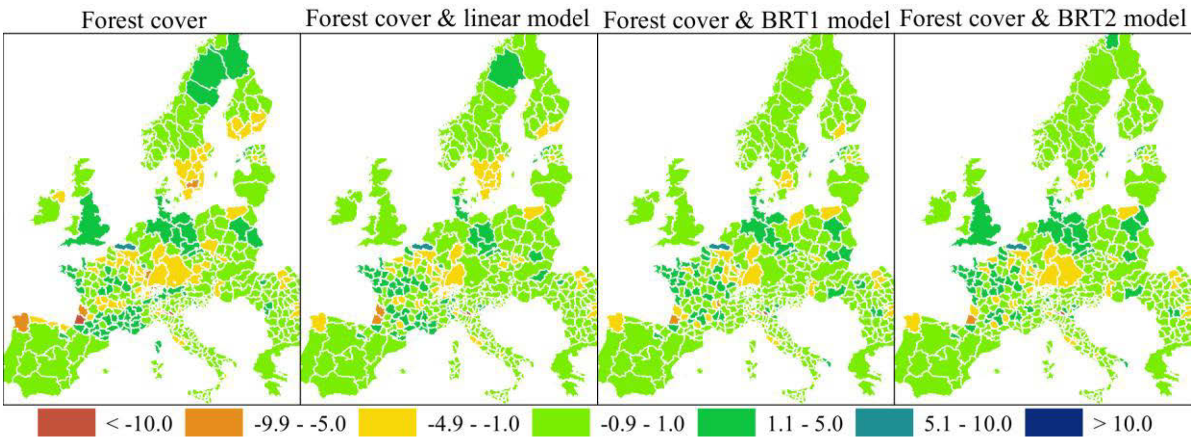


Figure III-6: Maps showing the difference between predicted and observed wood production [unit: m^3 ha^{-1} forest yr^{-1}] in Europe. National-level statistical data was disaggregated based on four different maps.

Figure III-6 provides information on the spatial patterns in the difference between predicted and observed levels of wood production in Europe. When considering forest cover only, wood production was overestimated in North Finland and Sweden, North-West Germany and South-East France, whereas wood production was underestimated in South Finland and Sweden, South-West of France, North-West of Spain and Southern parts of Germany. When combining forest cover with information derived from the linear and both BRT models, the absolute differences between predicted and observed data became smaller, but the spatial patterns in the differences between predicted and observed wood production remained similar.

3.3 Maps of wood production in European forests

Based on the verification described above, we used forest cover combined with information derived from the linear model to disaggregate statistics from administrative units to 1 × 1 km^2 grid maps. Considering location factors to disaggregate wood production statistics resulted in a greater variance in wood production at the grid-level, as compared to considering forest cover only (one-tailed F-test, $p<0.005$). At the European level, our maps (Figure III-7 and Figure SI III-4) reveal regions with very low levels of wood production (<0.1 m^3 ha^{-1} yr^{-1}), notably the coastal area of Norway, large parts of England, Spain, and Greece as well as northern and eastern Italy and the western parts of Netherlands and Belgium. Regions with high average levels of wood production (>5 m^3 ha^{-1} yr^{-1}) can be found in southern Sweden, southeast Belgium, northeast France, southern Germany and large parts of the Czech Republic, Austria and Switzerland and north-western Spain. Average harvest levels exceeded >10 m^3 ha^{-1} yr^{-1} in south-western France.

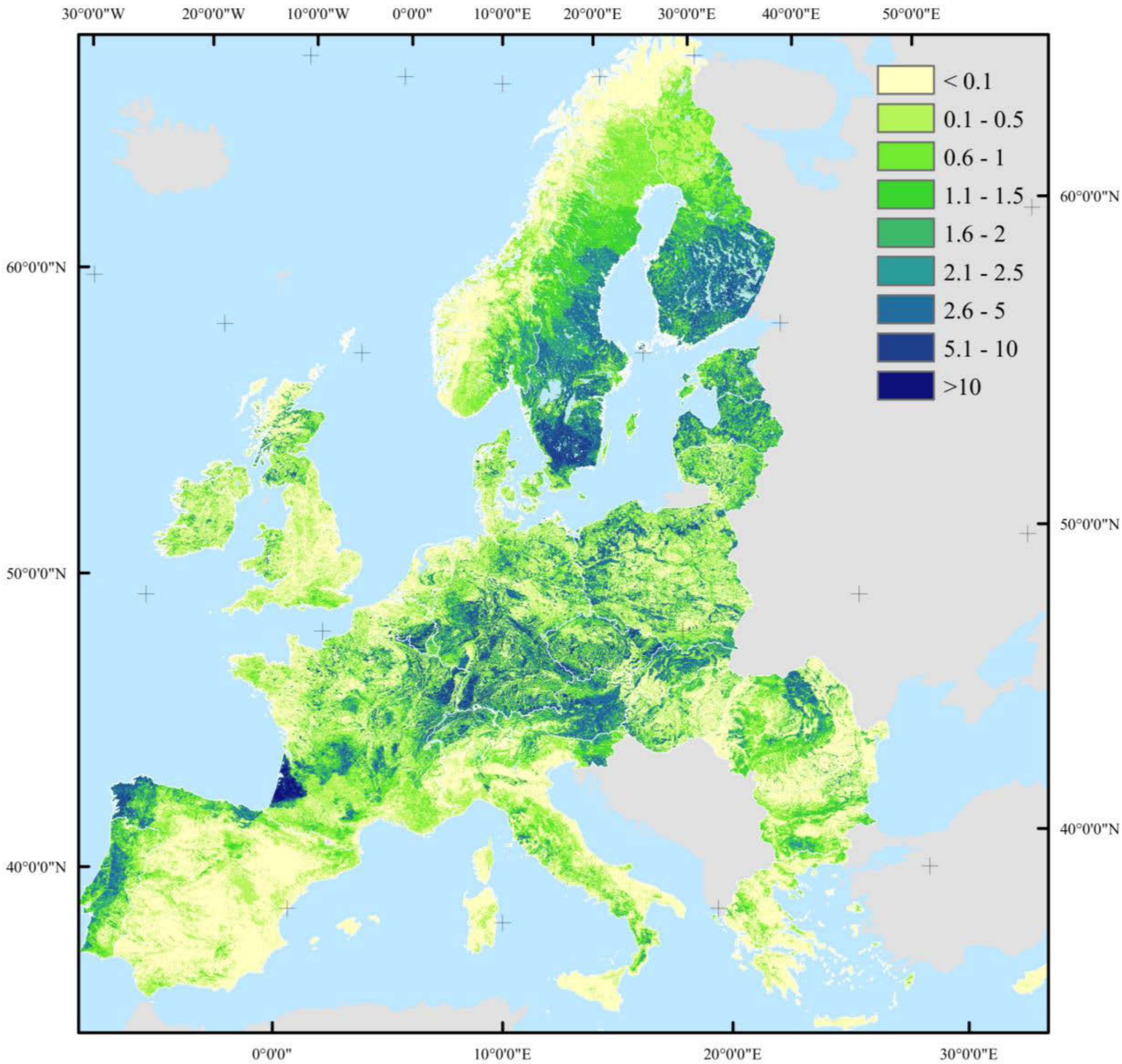


Figure III-7: Map showing predicted wood production [unit: m^3 ha^{-1} land yr^{-1}] in Europe averaged over the period 2000-2010. Statistics from administrative units were disaggregated to 1×1 km^2 raster maps with the linear model.

When looking at wood production in individual years (Figure SI III-4 and Figure SI III-5 in the Supplementary Information), we found that the level of wood production was relatively stable between years with small (<1 m^3 ha^{-1} yr^{-1}) negative or positive deviations from the average level of wood production. Large deviations were visible for southern Germany, northeast France and Switzerland in 2000, south Sweden in 2005, central Germany in 2007, and southwest France in 2009 and 2010.

4 Discussion

4.1 Location factors determining spatial patterns of wood production

Wood production is an important forest use and understanding the spatial patterns of harvesting is key for assessing how it might affect ecosystem services and biodiversity. Yet, wood production statistics are often only available for larger administrative units, requiring downscaling to assess the spatial patterns of harvesting. In this study we developed high-resolution wood production maps of European forests. We analysed the location factors of spatial patterns in wood production across a forest area of more than 163 million ha in Europe and found that increment, tree species composition, and terrain ruggedness were key location factors explaining patterns in wood production in Europe between 2000 and 2010. Other important location factors that we identified were growing stock volume, accessibility, precipitation amounts, as well as soil productivity. As such, our analysis of location factors that influence spatial patterns in wood production is in broad agreement with those reported by Levers et al. (2014), despite their focus on harvesting intensity (i.e., wood production in relation to the net annual increment) rather than wood production.

The identified location factors all relate to the costs and profitability of wood production, as harvest likelihood is higher under more productive growing conditions and in locations that can be more easily harvested. Our findings thus provide important information to further improve existing estimates of the costs of wood supply (cf. de Wit and Faaij 2010, Lauri et al. 2014). While there is a potential to increase wood or biomass production in Europe to meet future material and energy demands (Verkerk et al. 2011), it is not clear where such unutilised potentials are located. Based on our set of location factors that determine current wood production patterns, unutilised potentials are likely located in areas that have lower increment rates (resulting in lower harvest volumes or longer production cycles) and are more remote or rugged. This implies that the costs to mobilise these unutilised potentials could be higher compared to the costs for current wood production.

4.2 Spatial patterns of wood production

We disaggregated wood production statistics from the level of administrative units to raster maps with a resolution of 1×1 km^2. We show that forest cover alone is a poor proxy to map wood production, as wood production is not equally distributed across European forest landscapes. When considering forest cover only, we would underestimate wood production in productive, accessible regions and overestimate production in less productive and less accessible regions. When we included our harvest likelihood maps, the differences between predicted and observed wood production became smaller. For example, increment and soil productivity differences between regions (Figure SI III-1 in the Supplementary Information) explained the differences between predicted and observed wood production in Finland, Germany and Sweden, with northern regions in these countries generally having lower increment rates as compared to southern regions. In Finland, northern regions also had larger areas with less productive soils. In France and Spain plantation species (Figure SI III-1 in the Supplementary Information) explain why wood production was larger than average in southwest France and northwest Spain as compared to other regions in these countries.

Besides elucidating these broad differences in wood production patterns in Europe, our maps also provide insight into how wood production is distributed across forest landscapes at finer scale, within single administrative units, which is not possible based on statistical data only. We found that incorporating location factors in our disaggregation resulted in a greater variance in wood production at the grid-level, as compared to considering forest cover only. Because the provisioning of various ecosystem services is affected by wood production (Schwenk et al. 2012, Verkerk et al. 2014a, Zanchi et al. 2014), our maps therefore provide improved information on how other ecosystem services are affected by local differences in wood production.

Our time-series of wood production maps revealed few, but relatively large changes in wood production volumes locally (Figure SI III-4 and Figure SI III-5 in the Supplementary Information). For most of the cases, these large changes are likely the result of salvage harvest following big storm events. Locally, storm Lothar (December 1999; effect visible in 2000) affected southern Germany, northeast France and Switzerland, storm Gudrun (January 2005) affected southern Sweden, storm Kyrill (January 2007) affected especially central Germany, and storm Klaus (January 2009) affected southwest France (Gardiner et al. 2010). Our maps indicate the approximate location impacted by these storms (as well as other, less damaging storms) and thus allow to estimate changes in wood harvesting (and ecosystem service portfolios) associated with such storm events. Including data on storm tracks when generating harvest likelihood maps could be an interesting avenue for future research to better account for the effects of salvage harvests.

4.3 Comparison of regression models

We mapped wood production using likelihood maps derived from two regression techniques. Similar to Levers et al. (2014), the results of our BRT models indicated that some of the location factors were not linearly related to wood production (Figure III-2 and Figure III-3). However, accounting for non-linear relationships did not improve the disaggregation of wood production statistics in spite of a better model fit. An explanation for this could be the scale extrapolation that is inherent to dasymetric mapping. Our models were fitted on data at the level of administrative units, yet applied for the purpose of predictions to data at the pixel level. This assumes that the relationship between wood production and location factors remains the same across scales – from the level of administrative units to the grid level. This may be a bold assumption in the case of a flexible, non-linear model such as BRTs, which is able to model complex relationships that, however, may be less transferable across scales. Linear models instead use mean values that are likely more comparable over scales and that are less sensitive to scaling than non-linear relationships (Easterling 1997, Jelinski and Wu 1996). Thus, while our results suggest that BRTs represent a powerful technique to detect and investigate factors determining spatial patterns in wood production, including non-linear responses to location factors, simpler linear regression techniques may be more appropriate for dasymetric mapping, when statistical relationships are used to disaggregate statistics at finer resolutions.

4.4 Uncertainties in wood production maps

We mapped wood production based on official statistics. It is important to note that such statistics do not necessarily include all wood that is removed from forests. Trees may be harvested to produce firewood for own consumption and such wood removals may not be recorded in official statistics (Steierer 2010). This means that the mapped wood may be an underestimation.

Based on a literature review we identified a number of location factors that are associated with the spatial patterns in wood production. Only few of these location factors significantly explained wood production patterns. The share of protected forests was not found to affect wood production patterns, although it has been linked to a potential reduction in wood supply (Verkerk et al. 2014b). We explain such apparent discrepancies by gaps in available data. In the case of protected forests, we used spatially explicit data from two databases (IUCN and UNEP-WCMC 2012, EEA 2011). However, these datasets do not include all existing protected forests (Mac Sharry 2011), nor do they contain detailed information on restrictions applied to wood production. This means that although we did not find a predictor to significantly affect wood production in our regression analyses, it may still be a factor of relevance.

Likewise, some predictors we would have wished to include were not available in a consistent, spatially-explicit manner for the whole study area. An important factor that could help to explain the spatial patterns of wood production, but which was not considered here, relates to the location of and distance to wood processing facilities, including pulp- and sawmill and energy production facilities that use wood as a feedstock. We expect that higher levels of wood production could be observed closer to such facilities and production sites.

Our approach may have excluded local location factors that determine spatial variability in wood production across landscapes. The analysis of location factors at the level of larger administrative units can only partly account for factors that determine variations at the local to landscape level, e.g. environmental factors such as soil conditions, or socio-economic factors such as ownership. Despite these remaining uncertainties, our set of location factors explained a substantial part of the spatial variation in wood production and resulted in a robust disaggregation of wood production statistics, as verified by our comparison to the municipal level. The results of our validation of the regression-based likelihood maps do suggest that our wood production maps are well able to capture local patterns of wood production. However, while the accuracy assessment steps we carried out suggest our approach resulted in reliable wood production maps, we caution that we only had validation and verification data for some regions, from the Mediterranean to Scandinavia. A consistent and spatially detailed ground-based dataset on wood production is not readily available for Europe currently. We can thus not rule out the possibility that our map is less reliable in areas where we did not have such data. A harmonised, European-wide database with data from national forest inventories would be an invaluable data source for a future, more in-depth accuracy assessment.

5 Conclusion

We conclude that several location factors are important in explaining variation in wood production patterns across Europe: productivity, tree species composition and terrain ruggedness. Other important factors are growing stock volume, accessibility, precipitation amounts and site productivity. Incorporating such information significantly improves the disaggregation of wood production statistics from the regional level to the grid level as compared to disaggregation based on forest cover maps only. The final wood production maps give insight into forest ecosystem service provisioning and can be used to improve the assessment of potential and costs of woody biomass supply.

Acknowledgements

The authors thank Anze Japelj and Rok Pisek for providing data on regional wood production for Slovenia, Elena Rafailova for providing data on regional wood production for Bulgaria, Katja Gunia for providing statistics on forest area and net annual increment, Christoph Plutzar for providing data on terrain ruggedness and Mart-Jan Schelhaas and Geerten Hengeveld for comments on the methods. This work has been funded through the EU 7th framework projects VOLANTE and GHG-Europe (project numbers 265104 and 244122). Tobias Kuemmerle acknowledges funding by the Einstein Foundation Berlin, Germany. Opinions expressed in this paper are those of the authors only.

Supplementary Information

Figure SI III-1: Location factor maps. Maps showing values of location factors in 1 × 1 km raster maps. Units are explained in Table III-1.

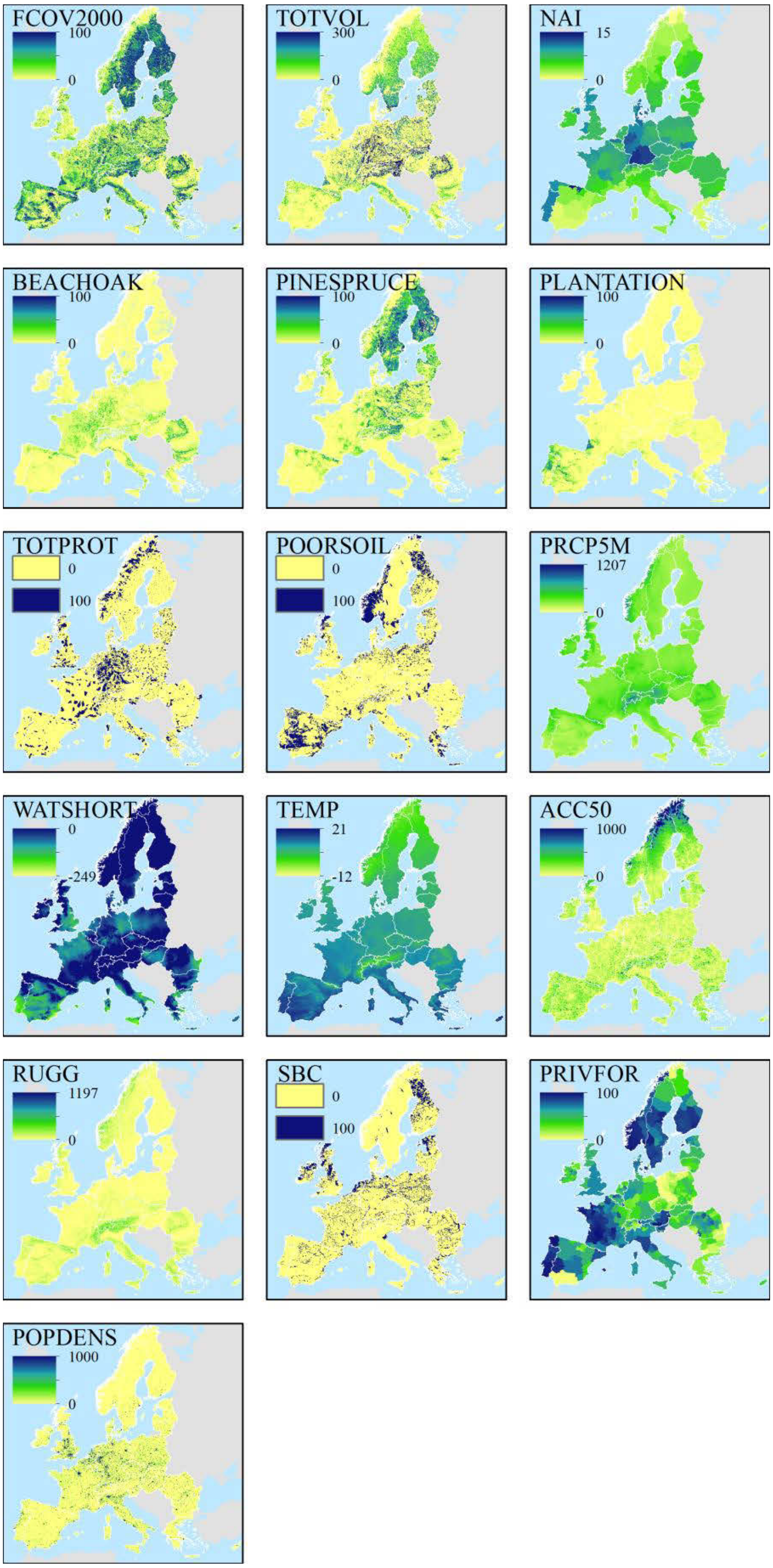


Figure SI III-2: Correlogram for the 16 location factors that were included in the statistical analyses. Upper panel: pie charts denoting the strength of the correlations with the colour indicating whether the correlation is positive (blue) or negative (red). Darker colours indicate stronger the correlations. Lower panel: correlation coefficients with confidence intervals.

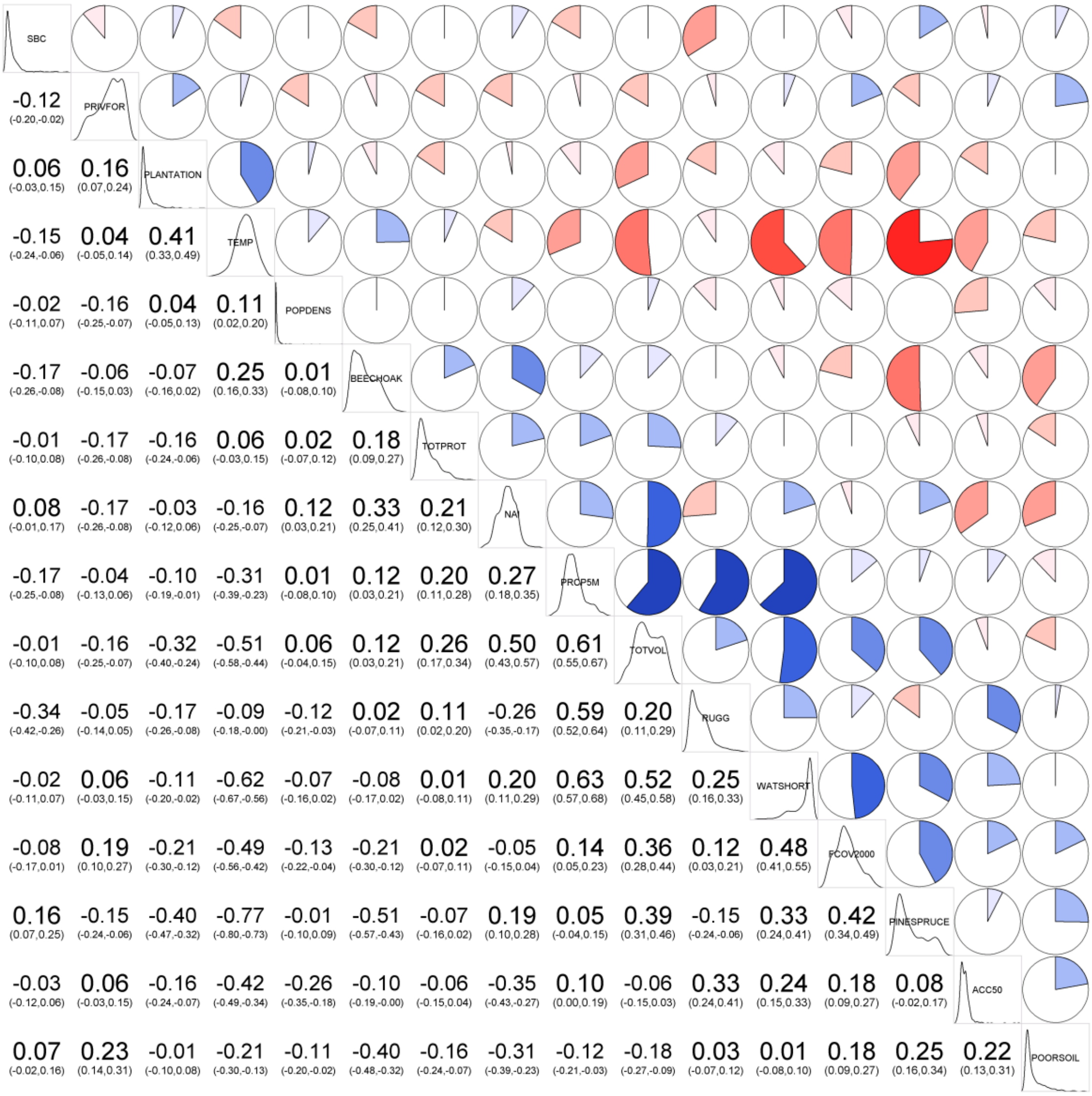


Figure SI III-3: Harvest likelihood maps. Maps show predicted harvest likelihood in Europe in 1 × 1 km raster maps for the three regression models.

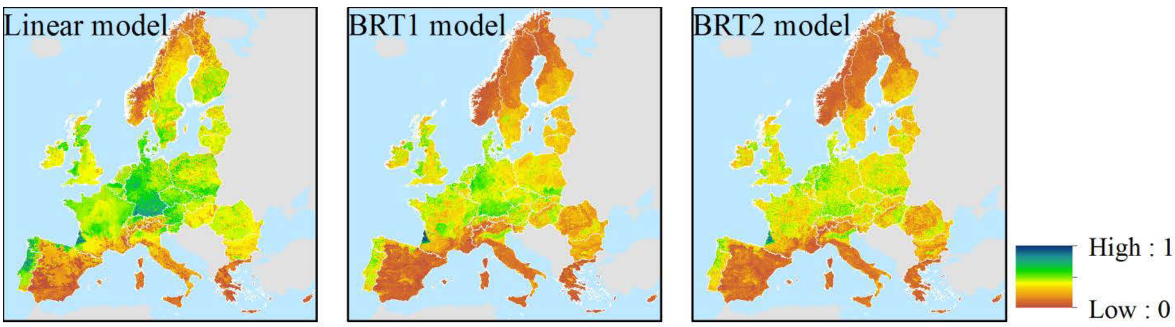


Figure SI III-4: Annual wood production maps. Maps show predicted wood production [unit: m^3 ha^{-1} land yr^{-1}] in Europe for each year for the period 2000-2010 by disaggregating statistics from administrative units to 1 × 1 km raster maps.

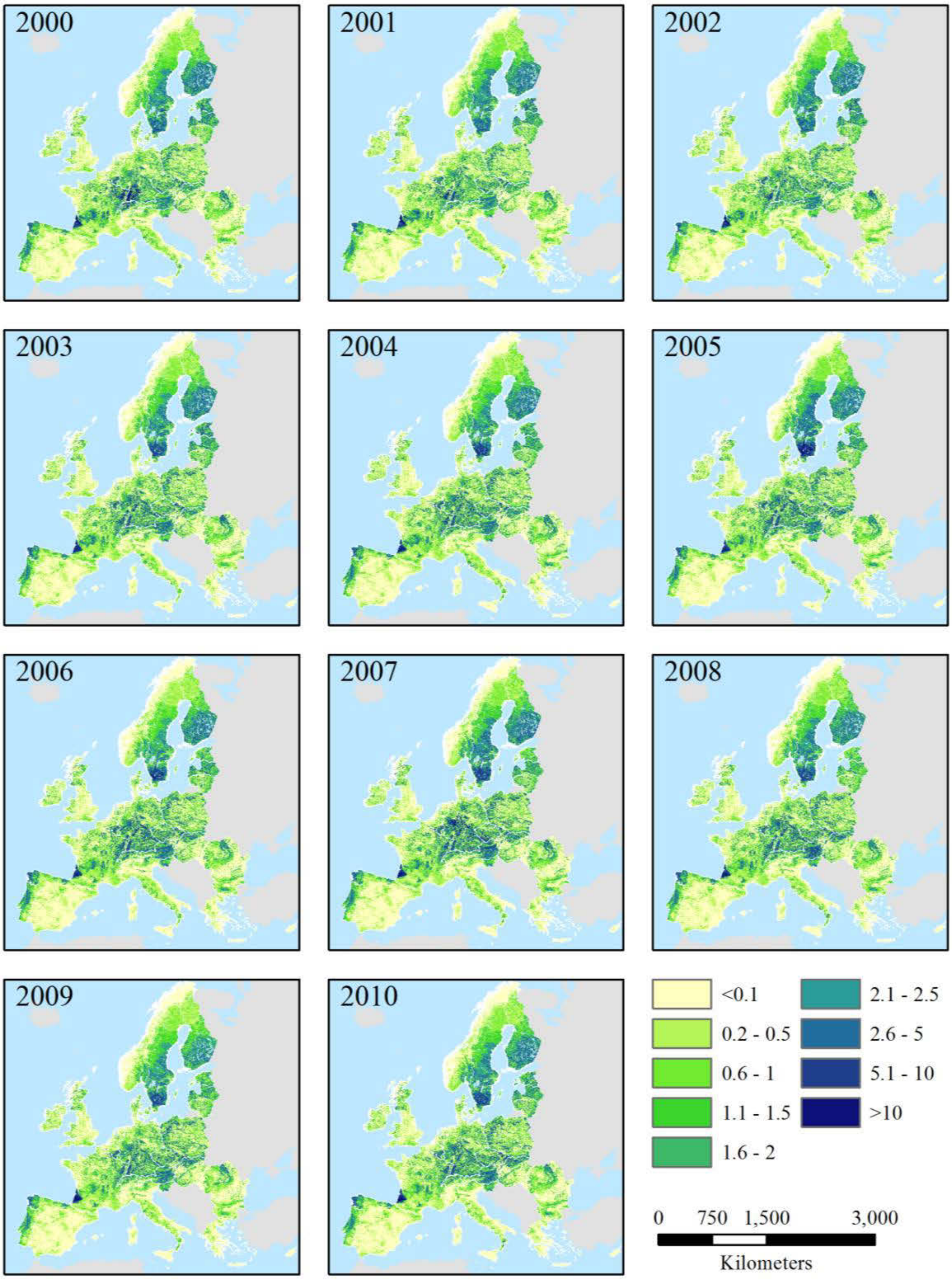
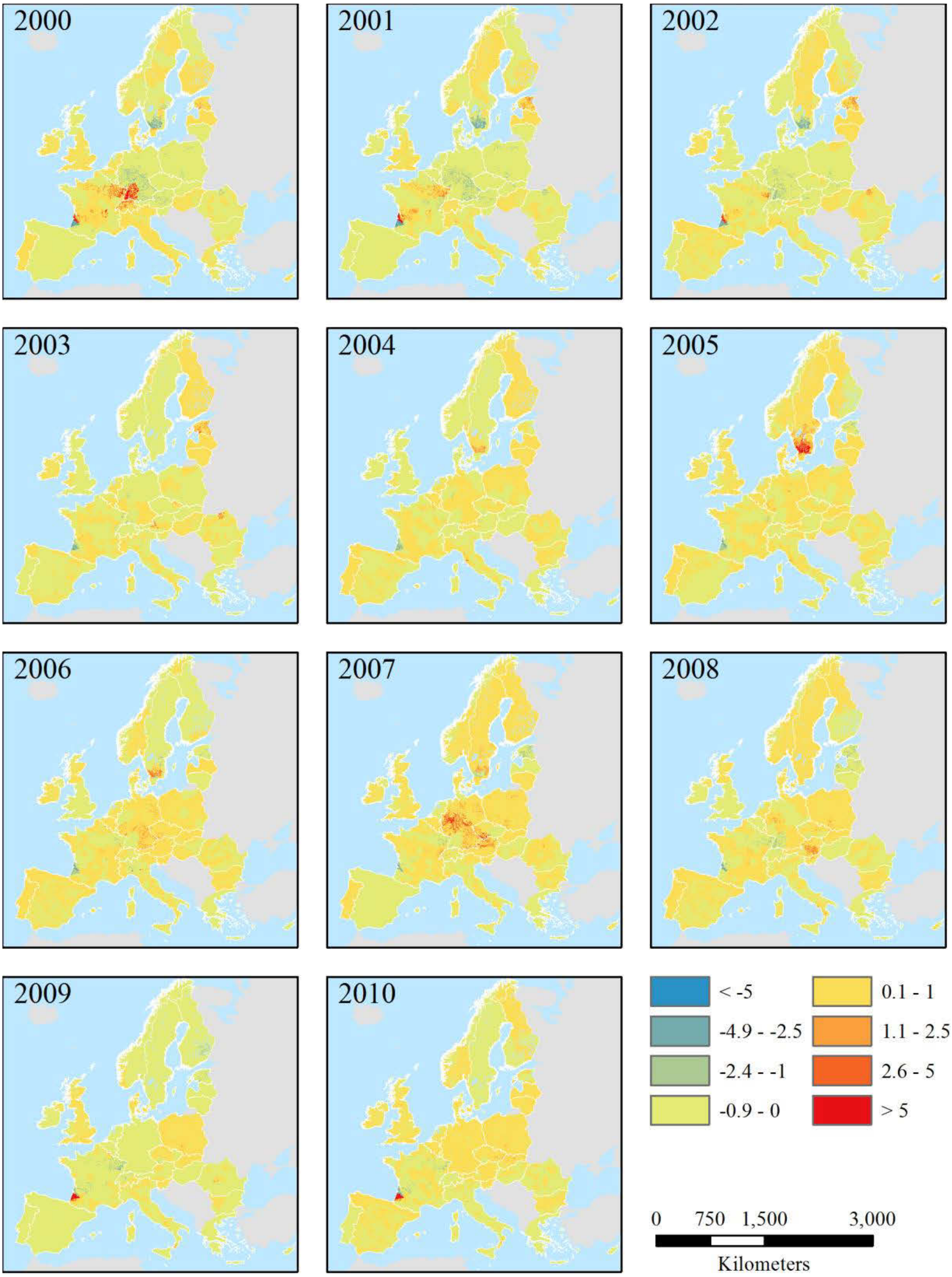


Figure SI III-5: Changes in annual wood production maps. Maps show deviations in predicted wood production [unit: m^3 ha^{-1} land yr^{-1}] in Europe for each year as compared to the average level of wood production over the period 2000-2010 in 1 × 1 km raster maps.



Chapter IV:
Drivers of changes in agricultural intensity in Europe

Agricultural Systems (in review)

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Abstract

The global demand for agricultural products will increase in the 21st century, unless major transformations in consumptive behaviour occur. Production increases in agriculture will to a large extent depend on intensifying existing agricultural systems. Yet, our understanding what determines the spatial patterns of agricultural intensity and changes therein is limited. Here, we analysed agricultural intensity changes in Europe focussing on yields and fertiliser application for six major crop-type groups for the period 1990–2007. We applied random effects panel regressions to analyse the spatial determinants of intensity changes using a suite of biophysical and socio-economic variables. We found that yields increased and mineral nitrogen application decreased by approximately 10%, suggesting a decoupling of output from input intensity in Europe's agricultural systems. Yields and nitrogen application across crop-type groups were particularly high in Western and Central Europe, whereas Eastern Europe was generally characterised by lower yields and nitrogen application. We found strong sub-national variation in intensity levels in respect to crop-type groups and indicator. Higher yields were typically related to higher fertilisation, high soil quality, less growing degree days, and high farm-economic performance. Higher nitrogen application rates, in turn, were related to high soil water and carbon contents, and high farm-economic performance. Our study provides insights into broad-scale intensity patterns and determinants of Europe's agricultural systems that allow for identifying trade-offs between agriculture and the environment as well as entry points for policy making in terms of regionalised, targeted policy measures towards a more sustainable management of Europe agricultural systems.

1 Introduction

Land use has affected more than 75% of the Earth's ice-free surface (Ellis and Ramankutty 2008), making land use a major driver of global environmental change (Verburg et al. 2015). Among land uses, agricultural areas are responsible for the largest environmental impacts of humans on natural systems (Kastner et al. 2012, Balmford et al. 2012), such as the widespread loss and degradation of ecosystems and biodiversity (Newbold et al. 2015), increased greenhouse gas emissions (Burney et al. 2010), or alterations of global nitrogen (Galloway et al. 2008) and phosphorus (Cordell et al. 2009) cycles.

Future population and consumption growth (Godfray 2014, Reisch et al. 2013) and the growing role of bioenergy crops (Beringer et al. 2011) will increase global demand for agricultural products over the next decades (Schneider et al. 2011, Wirsenius et al. 2010). As fertile land is becoming scarce (Lambin and Meyfroidt 2011) and further expanding agricultural areas will entail substantial trade-offs (Garnett et al. 2013, Eitelberg et al. 2015), future crop production increases will therefore have to come to a large extent from intensifying land already in use (Tilman et al. 2011). Yet, the intensification of agriculture is an understudied land-use change process (van Vliet et al. 2015b) and our knowledge on the patterns and drivers of agricultural intensification remains incomplete, especially at broad geographic scales (Erb 2012).

One reason for this knowledge gap is that agricultural intensity in itself is a complex phenomenon that can be measured in terms of input metrics (e.g., land, labour, use of fertilisers, pesticides, and machinery), output metrics (e.g., yields, caloric/protein/monetary value), or system metrics (e.g., yield gaps, human appropriated net primary production) (Erb et al. 2013a). While progress has recently been made in mapping spatial patterns of agricultural intensity (e.g., Fritz et al. 2015, Estel et al. 2015, Robinson et al. 2014, van Asselen and Verburg 2012, Temme and Verburg 2011, Neumann et al. 2010, Siebert et al. 2010, Monfreda et al. 2008) and identifying drivers of agricultural land-use change based on case-study evidence (van Vliet et al. 2015a), our knowledge about the drivers of changes in these patterns remains very limited across broad geographic scales (Kuemmerle et al. 2013).

Only a few studies have quantitatively assessed the determinants of patterns in agricultural intensity at broad geographic scales. While population and economic growth induced higher global fertiliser application rates (input metric) between 1960 and 2000 (Tilman et al. 2001), higher global caloric crop yields (output metric) were strongly associated with higher nitrogen inputs and to a lesser degree to higher precipitation, potential evapotranspiration, and elevation between 1965 and 2005. Higher soil pH values had a negative effect on crop yields whereas per capita GDP, as a measure of economic status, was positively related to crop yields in wealthier countries and negatively in poorer countries (Tilman et al. 2011). Global grain yields in the year 2000 were higher in areas closer to optimal temperature and higher precipitation, while higher efficiencies in grain production were related to higher fertiliser application, the presence of irrigation, market influence, and better accessibility (Neumann et al. 2010). At the global scale, agricultural intensification between 1990 and 2005, measured as yield to cultivated area ratio, was positively related to conservation/set-aside programs, cultivated areas, and cereal imports, and negatively related to gross agricultural production and agricultural work force (Rudel et al. 2009). Moreover, while global livestock distribution has been modelled (Robinson et al. 2014, FAO 2007), the importance of the explanatory factors remains unreported. Thus, although existing work highlights the value of broad-scale analyses for understanding patterns and changes of agricultural intensity, it remains unclear what drives intensity patterns at continental and regional scales.

Europe provides an interesting example to study drivers of changes in agricultural intensity due to several reasons. First, agricultural areas are widespread across the European Union, accounting for approximately half of the land surface (EC 2013a, Stoate et al. 2009). Second, most agricultural land-use change in Europe occurred along intensification gradients over the last decades, while the net agricultural area remained nearly stable (Rounsevell et al. 2012). Third, agricultural intensity varies substantially across Europe due to the pronounced differences in environmental conditions (e.g., boreal to Mediterranean), history (e.g., capitalism vs. socialism), ethnic composition, and economic status (highly industrialised vs. less industrialised economies) (Jepsen et al. 2015). How this heterogeneity relates to changes in the spatial patterns of agricultural intensity, however, remains unclear.

Studies that focus on patterns and determinants of agricultural intensity in Europe are rare and were often restricted in space (e.g., only for the EU15) or time (e.g., only one target year). Existing work also typically focussed on a single intensity indicator, a limited number of crop types, and either arable areas or grasslands. For example, lower arable land-use intensity and higher grassland intensity in terms of nitrogen application in five European countries for the year 2000 were related to inferior accessibility and soil conditions, as well as water shortage (Temme and Verburg 2011). Yields of selected crops increased across the EU15 between 1990 and 2003 with increasing economic size (i.e., standard gross margins), inputs (e.g., fertiliser, irrigation), share of arable land, and crop-type specialisation (Reidsma et al. 2009). Similarly, high elevation and less-favoured areas negatively affected crop yields, while temperature and precipitation were often related in concave ways to yields (Reidsma et al. 2010, Reidsma et al. 2007). Finally, higher livestock occurrence were related to higher precipitation, lower relief energy, better soils, and favourable landscape configuration (Neumann et al. 2009). Despite these efforts, a knowledge gap remains regarding the determinants of the agricultural intensity change in Europe, especially since the 2000s, when the EU expanded eastwards.

The overall objective of this paper was to provide improved insights into the patterns and broad-scale spatial determinants of agricultural intensity changes in the European Union (EU27) between 1990 and 2007. As intensity metrics, we used yields and nitrogen application rates of six crop-type groups including grasslands. As explanatory factors, we relied on environmental, demographic, and socio-economic conditions. Specifically, we ask the following research questions:

1. What were the spatiotemporal patterns of yields and nitrogen application in Europe between 1990 and 2007?
2. Which spatial determinants describe these patterns and trends best?
3. How does the importance and relationship of spatial determinants vary between crop-type groups and between agricultural input- and output-intensity metrics?

2 Material and methods

2.1 Agricultural intensity indicators

To assess agricultural intensity across Europe, we used yields and mineral nitrogen application [kg ha^{-1}] (Table IV-1) from the Common Agricultural Policy Regionalised Impact (CAPRI) Modelling System database (Britz and Witzke 2014), which provides the most comprehensive set of indicators on agricultural management intensity in Europe based on official data from the European Union (Eurostat). We focused on mineral nitrogen application only, as it is the main capital-related input to agricultural areas (EC 2015a). The CAPRI database provides gap-filled and harmonised information on the management

Table IV-1: Overview of target and explanatory variables and their descriptive statistics. Explanatory variables marked with an asterisk were included as linear and quadratic terms in the regression model. Expected directions of influence are separated for yields (first sign) and nitrogen application (second sign).

Group	*Variable*	*Description*	*Unit*	*Year*	*Source*	*Sign*	*Format*	*Res*
Target	yields	Crop production per area	kg ha^{-1}	8 panels	Britz and Witzke 2014	•	V,D	•
	nitrogen application	Application of mineral nitrogen fertiliser per area	kg ha^{-1}	8 panels	Britz and Witzke 2014	•	V,D	•
Farm and farmer characteristics	field_size	Interpolation of field size categories ranging from 10 (very small) to 40 (large)	•	•	Fritz et al. 2015	+|+	R,S	$1km^2$
	sgm	Annual working units (one person working full-time)	#	8 panels	EC 2015c	-|-	V,D	•
	holdings_ uaar	Number of holdings per utilised agricultural area	# ha^{-1}	8 panels	EC 2015c	-|-	V,D	•
	croparea_ uaar	Area share of crop-type groups from total utilised agricultural area	%	8 panels	EC 2015c	+|+	V,D	•
Micro- ecomomy	fert_uaar	Expenses for fertilisers per utilised agricultural area	€ ha^{-1}	8 panels	EC 2015c	+|+	V,D	•
	fnv_awu	Farmer's income (ratio of farm net value added and labour input)	€ a wu^{-1}	8 panels	EC 2015c	+|+	V,D	•
Access	acc50*	Travel time to cities > 50,000 inhabitants	min	2000	Nelson 2008	-|-	R,S	$1km^2$
	rugg	Terrain ruggedness expressing relief energy	m		Own calc., Jarvis et al. 2008, Riley et al. 1999	-|-	R,S	$1km^2$
Soil	soil_pH	Soil pH values	•	2006	Panagos et al. 2012, EC 2010	•	R,S	$1km^2$
	soc_topsoil_ tc*	Soil organic carbon stock in agricultural soils in 0-30 cm soil depth	tC ha^{-1}	2010	Lugato et al. 2014a, Lugato et al. 2014b, Panagos et al. 2012	+|+	R,S	$1km^2$
	swap	Soil water availability for plants	mm		EC 2006b	+|+	R,S	$1km^2$
Climate	gdd*	Growing degree days (calculated based on daily mean temperatures with 10°C as base temperature)	#	8 panels	Haylock et al. 2008	-|-	R,D	0.25 °
	prcp_sum_ year*	Annual precipitation sum	mm	8 panels	Haylock et al. 2008	+|+	R,D	0.25 °
Macro-level	popdens*	Population density	pers km^{-2}	8 panels	EC 2015c	-|-	V,D	•
	country	Country dummy to capture country specific information (enumeration from north to south)	•	•	Own specification	•	V,S	•
	time	Time dummy to capture time-step specific information	•	•	Own specification	•	V,S	•

intensity of agricultural areas across Europe that is complemented where needed by national-level data for the most recent member states to extend time series back in time (Britz and Witzke 2014, c.f. Text SI IV-1 in the Supplementary Information).

We joined the CAPRI data to the respective NUTS (Nomenclature des unités territoriales statistiques, i.e., Nomenclature of Territorial Units for Statistics) regions and calculated annual agricultural intensity indicators for subnational (19 countries) and national (6 countries) administrative units from 1990 to 2007 (Table SI IV-1). Subnational units represent regions with 3 to 7 million inhabitants (NUTS1) and 0.8 to 3 million inhabitants (NUTS2). To consider crop-specific characteristics, we calculated intensity indicators for six crop-type groups separately (see Table SI IV-1 for national area coverage), following the stratification of Kempen et al. (2005): *cereal crops* (soft wheat, durum wheat, rye and meslin, barley, oats, maize, paddy rice, and other cereals), *fodder crops* (grass, fodder maize, fodder root crops, and other food from arable land), *industrial crops* (potatoes, sugar beet, textile crops, and other industrial crops), *labour-intensive crops* (flowers, tobacco, tomatoes, and other vegetables), *oilseeds and pulses* (rape seed, sunflower, soya, and pulses), and *permanent crops* (olives, nurseries, vine, citrus fruits, and other fruits). This decomposition was necessary due to substantial differences in yield and fertiliser application across crop-type groups, and to account for differences between arable land and grasslands.

We excluded overseas and island NUTS regions not covered by the Common Agricultural Policy Regionalised Impact - The Dynamic and Spatial Dimension (CAPRI DynaSpat) crop-cover database (see section 2.2). This resulted in a total of 220 administrative units that we considered for analysis. Subsequently, we checked for missing years in the target datasets and excluded regions with data in less than half of the time steps or missing data in three or more consecutive time steps. We filled remaining data gaps (1.6% and 4% of all observations across crop-type groups for yields and nitrogen application, respectively) either by interpolation or by using the first or last value in the time series in cases where gaps occurred at the beginning or end of the time series. Our final target dataset contained 203 observations for oilseeds and pulses, 212 observations for labour-intensive crops, 218 observations for permanent crops, and 220 observations for cereals, fodder, and industrial crops.

2.2 Explanatory variables

To identify variables that were assumed to influence agricultural intensity patterns, we relied on recent reviews on drivers and determinants of agricultural land-use change (van Vliet et al. 2015a, Hazell and Wood 2008), as well as prior work on agricultural intensity patterns in Europe (Reidsma et al. 2007, Reidsma et al. 2010, Reidsma et al. 2009). We hypothesized a relationship between agricultural intensity (i.e., yields and fertiliser use) and each spatial determinant (Table IV-1). For a detailed description of the variable selection and data sources, see Text SI IV-2 in the Supplementary Information.

We identified 16 potential explanatory variables representing six broad groups: (i) farm characteristics, (ii) micro-level economic conditions, (iii) accessibility, (iv) soil conditions, (v) climatic conditions, and (vi) macro-level conditions. For the latter, we used population density as well as country and time dummies to account for unobserved differences in countries, such as national policies and culture and temporal trends. We aggregated all explanatory variables to the administrative units on which yields and fertiliser input were reported. To do so, we first re-projected all raster layers into the Lambert Azimuthal Equal Area projection and resampled data to a 1x1 km^2 grid using bilinear resampling for all continuous and nearest neighbour resampling for all categorical variables. Subsequently, we aggregated variables using a weighting approach that considered the spatial coverage of each crop-type group. We did this because our focus was on explaining the variability of conditions in areas covered by a specific crop-type group, which can be small for a given administrative unit, and not on explaining the general conditions within an administrative unit. To do so, we multiplied each explanatory variable with a continuously-scaled grid representing the spatial coverage of each crop-type group (CAPRI-DynaSpat at 1-km resolution for the year 2000; Leip et al. 2008).

2.3 Regression analyses

Regression models are powerful tools to assess the drivers and determinants of changes in land-use patterns (Levers et al. 2014, Müller et al. 2013). Panel regressions are particularly well-suited to do so as they can control for latent time-invariant, unobserved heterogeneity (i.e., omitted explanatory variables). This is a major advantage for land-use assessments because consistent measurements across time and space are often lacking for potentially important explanatory variables. We used random effects panel regressions to relate our two agricultural intensity indicators to the explanatory variables (Table IV-1).

Random effects models are highly suitable to investigate phenomena that change over time. Often, these data sets are unbalanced due to considerable variation in number and timing of observations and the uncontrollability of the circumstances under which measurements were taken, restricting the use of traditional multiple linear regressions (Laird and Ware 1982). Random effects models assume that the time-invariant, unobserved heterogeneity (i.e., the error term) is uncorrelated with the explanatory variables and hence treated as a random variable in the model, in contrast to fixed effects models where it is treated as a parameter (Gardiner et al. 2009). Furthermore, random effects models allow for explicit modelling and analysis of between- and within-variations among observations (Laird and Ware 1982).

We set up separate models for yields and fertiliser application per crop-type group, resulting in a total of 12 models. Since not all explanatory variables were available as annual time series with full spatial coverage as required by random effects models, we had to exclude Belgium, Slovenia, and Spain from the regression analysis as well as those years for which information on explanatory variables was missing. Our consistent and area-wide dataset used in the regression analysis covered 164 (oilseeds and pulses) to 178 (cereal, fodder, and industrial crops) observations and the years 1990, 1993, 1995, 1997, 2000, 2003, 2005, and 2007. We checked for non-linearity between explanatory variables and targets, and included explanatory variables revealing a non-linear relationship as linear and centred quadratic terms. We calculated Spearman ρ values between all explanatory variables (Table SI IV-2) to investigate possible collinearity. We checked variable pairs where ρ exceeded 0.8 and excluded the explanatory variable that had a weaker correlation with the target. In the final data set, five variable pairs exceeded $\rho > 0.7$ while none exceeded $\rho > 0.8$, thus indicating no major collinearity problems. Model fits were estimated using R^2 values for within, between, and overall effects of which the overall R^2 was used to assess model performance. We used panel model z-values to assess the importance of each explanatory variable within our models, robust standard errors to deal with possible heteroscedasticity, and Moran's I (Moran 1950) to assess spatial autocorrelation of residuals. We considered an explanatory variable as significant if its p-value was below 0.1. We created predicted margins plots at nine quantiles (5% to 95% quantile in 10% intervals) to describe the form and direction of the relationship between target and explanatory variables along its data range. All analyses were performed with the *xtreg* command in STATA (StataCorp 2013) and all post-processing was done in R (R Core Team 2014).

3 Results

3.1 Spatio-temporal patterns of agricultural intensity in Europe

Between 1990 and 2007, EU-wide yields for all six crop-type groups combined (total crops) increased by approximately 10% (Figure IV-1, left panel) corresponding to a mean annual increase of 0.58% (s.d. = 2.27%). Industrial and labour-intensive crop yields increased most strongly (by 21.25% and 37.95%, respectively), and revealed the highest yield levels among all crop-type groups we explored. Fodder crop (14.65%) and permanent crop (12.50%) yields increased to a lesser degree, whereas yields for cereal crops (3.68%) as well as for oilseeds and pulses (2.56%) remained fairly stable at comparably low yields.

However, yield trends for each country and crop-type group and did not always follow the EU-wide trend (cf. Figure SI IV-1). For example, in some countries overall crop yields were stable (e.g., Netherlands or Denmark) or even declining (e.g., Bulgaria or Poland) over the study period. Similarly, industrial and labour-intensive crops did not consistently show the strongest increases (e.g., Ireland or Belgium) and even declined (e.g., Finland or Sweden). Among crop-type groups, yield levels were largely in line with EU-wide patterns with a few exceptions (e.g., highest yields for permanent crops in the Netherlands and Belgium or high fodder yields in Ireland and Latvia). Generally, yields across crop-type groups were generally higher and showed clearer increasing trends in Western European countries, especially in the EU15 countries, compared to countries in Europe's east, which even had decreasing yields.

Mineral nitrogen application in the EU decreased by about 10% for all six crop-type groups combined (Figure IV-1, right panel) with a mean annual decrease of -0.63% (s.d. = 2.61%). After a marked decrease in the early 1990s, nitrogen application levels increased in the late 1990s followed again by a monotonic decrease after 2000. This trend was observable for all crop-type groups, except for oilseeds and pulses that experienced a steady increase after the mid-1990s (15.96%). Fodder crops had the strongest decrease (-27.61%) followed by permanent crops (-5.62%), both having the comparably lowest nitrogen application rates we explored. Nitrogen application for cereal, labour-intensive, and industrial crops remained approximately stable (-3.83% to -0.06%) but had the highest application levels observed.

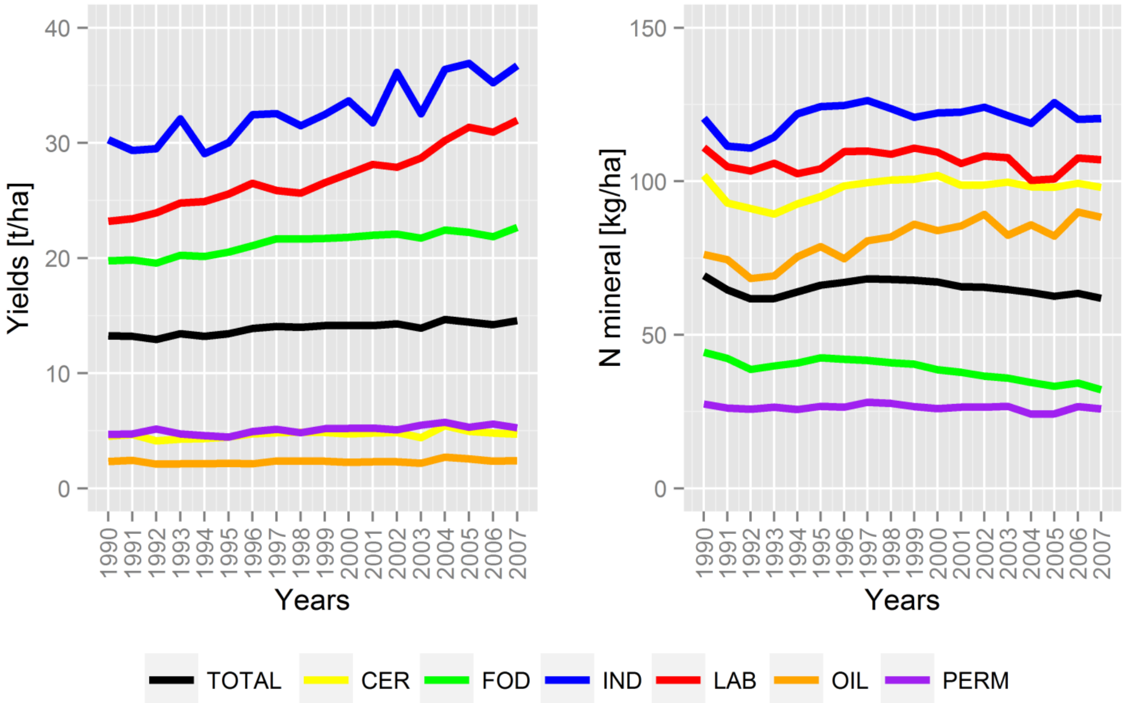

Figure IV-1: Time series of yields [t ha^{-1}] (left panel) and mineral nitrogen application [kg ha^{-1}] (right panel) for the EU between 1990 and 2007. Crop-type groups are cereal crops (CER), fodder crops (FOD), industrial crops (IND), labour-intensive crops (IND), oilseeds and pulses (OIL), and permanent crops (PERM) and their aggregate total (TOTAL).

Nitrogen application rates also showed characteristic trends for each country and crop-type group (Figure SI IV-2). For example, in some countries total nitrogen application was approximately stable (e.g., Sweden or Spain) or even – and partly strongly – increasing (e.g., Poland or Slovakia), contrary to EU-wide trends. Also, temporal dynamics of fodder crops (e.g., Belgium or Sweden) and oilseeds and pulses (e.g., Czech Republic) were highly variable and deviated from the overall strong decreases (fodder) or increases (oilseeds and pulses). Among crop-type groups, nitrogen application levels were largely in line with EU-wide patterns. Generally, nitrogen application rates across crop-type groups were higher in Western European countries compared to countries in Europe's east. However, Western and Central European countries generally showed decreasing nitrogen application rates in contrast to Eastern European countries, where nitrogen application was often increasing during our study period, though not reaching the levels of Western and Central Europe.

Overlaying subnational patterns of yields and nitrogen application confirmed the general, country-level pattern of high agricultural intensity across all six crop-type groups in Western and Central Europe, compared to lower-intensity in the remainder, especially in

Eastern Europe (Figure IV-2). Regions with high values for both intensity indicators were rare and occurred, for example, in Northern France and Germany (cereal crops) or in the Netherlands and Northern Sweden (labour-intensive crops). Generally, though regions were characterised by only one dominant intensity indicator, for example for yields in South-Western France and Northern Italy (cereal crops, oilseeds and pulses) and parts of Northern Germany, Italy, and France (industrial crops) or for nitrogen application rates in Northern Sweden and Finland (fodder crops) and Southern Germany and Northern UK (oilseeds and pulses).

3.2 Variables explaining changes in agricultural intensity in Europe

The explanatory power of the six crop-type group models for yields ranged from $R^2 = 0.66$ for industrial and labour-intensive crops to $R^2 = 0.94$ for permanent crops. Explanatory power was somewhat lower for nitrogen application models, ranging from $R^2 = 0.47$ for industrial crops to $R^2 = 0.68$ for cereal crops (Table IV-2). Residuals were mostly normally distributed, except for fodder and permanent crops that had a slightly skewed and

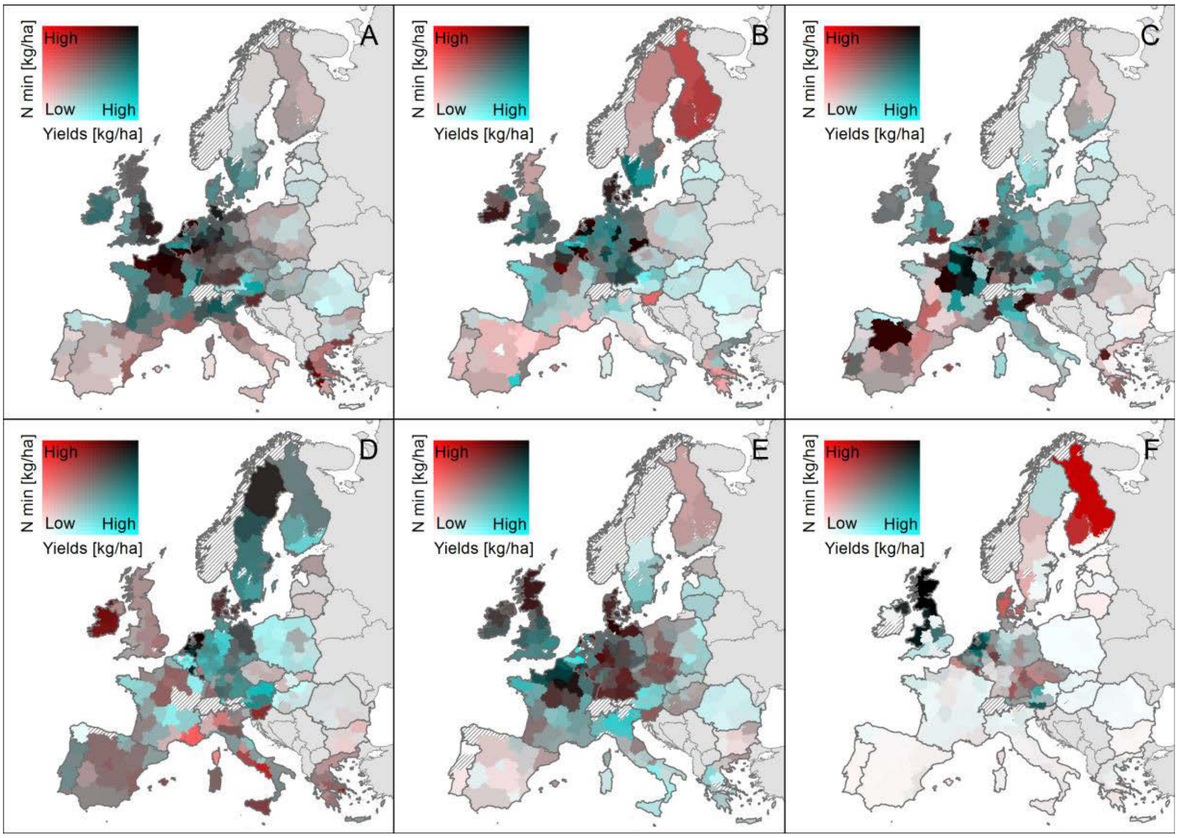

Figure IV-2: Concordance maps of mean yields [kg ha^{-1}] and fertiliser application [kg ha^{-1}] in the EU between 1990 and 2007. Panel labels refer to cereals (A), fodder crops (B), industrial crops (C), labour-intensive crops (D), oilseeds and pulses (E), and permanent crops (F). Values were z-transformed. Bright blue colours indicate high yields, bright red colours indicate high fertiliser application, white and black colours indicate low and high values, respectively, for both variables. Hatched areas represent NUTS regions that were excluded from the analysis due to data gaps.

Table IV-2: Model fit and variable importance for all models. All explanatory variables with p-values < 0.1 were selected. Plus (+) signs indicate a positive effect on the target variable, minus (-) signs a negative effect. Explanatory variables that entered the model as linear and quadratic term are marked with asterisks and signs are provided for both terms (linear|quadratic) with insignificant terms in parentheses. Detailed information on panel model regression coefficients, standard errors, and significance levels are provided in Table SI IV-3 and Table SI IV-4 in the Supplementary Information.

<table>
<tr><th></th><th rowspan="2">SUMMARY</th><th colspan="6">YIELDS</th><th colspan="6">NITROGEN</th></tr>
<tr><th></th><th>cer</th><th>fodd</th><th>ind</th><th>lab</th><th>oil</th><th>perm</th><th>cer</th><th>fodd</th><th>ind</th><th>lab</th><th>oil</th><th>perm</th></tr>
<tr><td rowspan="5">MODEL FIT</td><td>within R²</td><td>0.27</td><td>0.85</td><td>0.25</td><td>0.12</td><td>0.14</td><td>0.10</td><td>0.12</td><td>0.33</td><td>0.08</td><td>0.08</td><td>0.07</td><td>0.03</td></tr>
<tr><td>between R²</td><td>0.85</td><td>0.77</td><td>0.72</td><td>0.81</td><td>0.83</td><td>0.97</td><td>0.76</td><td>0.75</td><td>0.57</td><td>0.80</td><td>0.73</td><td>0.70</td></tr>
<tr><td>overall R²</td><td>0.79</td><td>0.79</td><td>0.66</td><td>0.66</td><td>0.72</td><td>0.94</td><td>0.68</td><td>0.66</td><td>0.47</td><td>0.61</td><td>0.58</td><td>0.58</td></tr>
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<tr><td rowspan="15">EXPLANATORY VARIABLE IMPACT</td><td>nitrogen appl.</td><td>+</td><td>+</td><td>+</td><td>+</td><td>-</td><td>+</td><td>NA</td><td>NA</td><td>NA</td><td>NA</td><td>NA</td><td>NA</td></tr>
<tr><td>field_size</td><td></td><td></td><td>+</td><td></td><td>+</td><td></td><td>+</td><td></td><td></td><td></td><td>+</td><td>-</td></tr>
<tr><td>sgm</td><td></td><td>-</td><td></td><td>+</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>holdings_uaar</td><td></td><td>+</td><td>-</td><td></td><td></td><td></td><td></td><td></td><td></td><td>+</td><td></td><td></td></tr>
<tr><td>croparea_uaar</td><td></td><td></td><td></td><td>+</td><td>+</td><td>-</td><td>+</td><td></td><td></td><td>+</td><td>+</td><td></td></tr>
<tr><td>fert_uaar</td><td>+</td><td>+</td><td></td><td></td><td></td><td></td><td></td><td>+</td><td></td><td></td><td></td><td>+</td></tr>
<tr><td>fnv_awu</td><td>+</td><td></td><td></td><td></td><td>+</td><td>-</td><td></td><td></td><td></td><td>+</td><td>+</td><td></td></tr>
<tr><td>acc50*</td><td>-|+</td><td></td><td></td><td></td><td>(-)|+</td><td></td><td></td><td></td><td></td><td>+|-</td><td></td><td></td></tr>
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<tr><td>soil_pH</td><td>-</td><td></td><td></td><td></td><td>-</td><td></td><td></td><td></td><td>-</td><td></td><td></td><td></td></tr>
<tr><td>soc_topsoil_tc*</td><td></td><td>+|(-)</td><td></td><td></td><td></td><td>+|(-)</td><td>+|-</td><td>+|-</td><td></td><td></td><td>+|(+)</td><td>+|-</td></tr>
<tr><td>swap</td><td>+</td><td></td><td>+</td><td>-</td><td>+</td><td></td><td>+</td><td>+</td><td>+</td><td></td><td></td><td></td></tr>
<tr><td>gdd*</td><td>-|-</td><td></td><td>-|-</td><td>-|(+)</td><td>-|-</td><td>-|(+)</td><td>(-)|-</td><td></td><td></td><td>(+)|+</td><td></td><td>-|+</td></tr>
<tr><td>prcp_sum_year*</td><td>(+)|-</td><td></td><td>+|(-)</td><td></td><td></td><td>+|(+)</td><td></td><td>-|(-)</td><td></td><td></td><td></td><td></td></tr>
<tr><td>popdens*</td><td></td><td></td><td>+|(-)</td><td></td><td>+|-</td><td></td><td></td><td></td><td></td><td></td><td></td><td>(-)|+</td></tr>
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leptokurtic distribution. We found low levels of spatial autocorrelation within model residuals (Griffith 2009) for yields (I = 0.14 – 0.28) and for nitrogen application rates (I = 0.19 – 0.39), except for permanent crop yields (I = 0.70).

Depending on the crop-type group, different explanatory variables were important (Table IV-2; detailed results in Table SI IV-3 and Table SI IV-4). Variables from all groups showed significant effects on yields for cereals as well as oilseeds and pulses, whereas fodder yields were mainly explained by micro-economic conditions. Farm characteristics, climatic, soil, and micro-economic conditions were the most dominant factors for explaining industrial crop yields, similar to labour-intensive and permanent crop yields.

Across all crop-type groups, seven explanatory variables were significantly related to yields in at least half of the models (Table IV-2 and Figure IV-3).

Higher nitrogen application rates generally affected crop yields positively, with the highest leverage effect for fodder and permanent crops. Higher crop specialisation (croparea_uaar) was positively related to yields from labour-intensive crops and oilseeds and pulses, while the remaining crop-type groups showed decreasing or stable yields with increasing crop coverage per utilise agricultural area. Higher farm economic performance (fnv_awu) was generally positively related to yields, except for fodder and permanent crops. Soil water

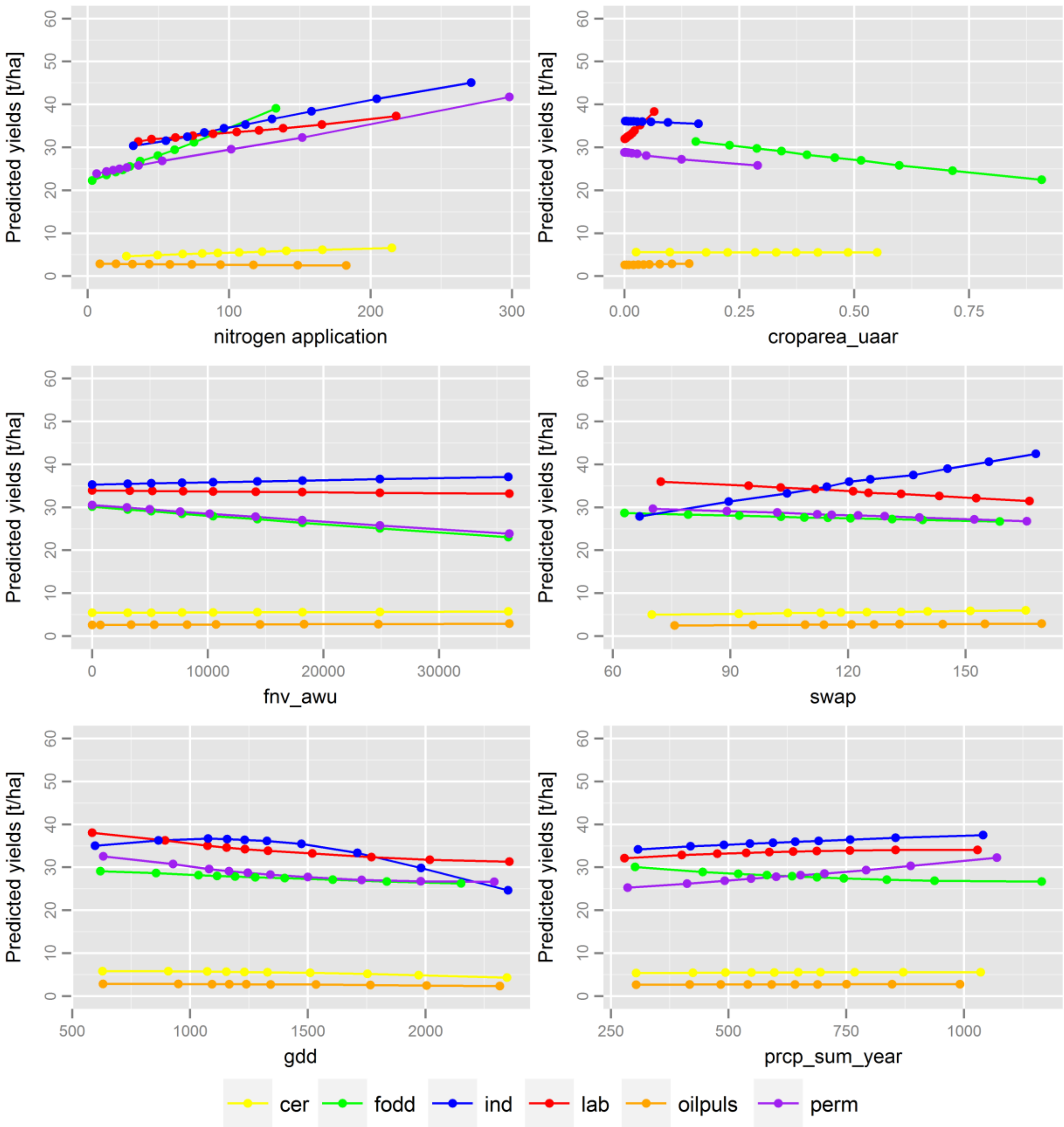

Figure IV-3: Predicted margin plots for yields [t ha^{-1}] across all six crop-type groups for the most important explanatory variables. Variables were: applied nitrogen, crop-area per utilised agricultural area, economic performance, soil water availability, growing degree days, and annual precipitation sums (terrain ruggedness was excluded).

availability (swap) was positively related to crop yields for cereal and industrial crops, as well as for oilseeds and pulses but negatively related to the remaining crop-type groups. Annual precipitation sums (prcp_sum_year) revealed a generally positive effect on crop yields while our results showed that growing degree days (gdd) had a negative, though generally marginal, effect on crop yields, especially for industrial crops.

Overall, predicted yield margins were consistently lowest for cereal crops as well as oilseeds and pulses, while labour-intensive and industrial crop yields were highest. Cereal crops, as well as oilseeds and pulses, also showed the lowest absolute variability for predicted yield margins, while the other crop-type groups showed high variability for certain explanatory variables. Country-specific effects on yields were evident for permanent crops with high yields especially for the Netherlands and UK, and to a lesser degree for industrial crops (Denmark, Italy, and Portugal) and labour-intensive crops (Austria, Germany, and the Netherlands). Time-dependent effects showed increasing yields over time particularly for industrial, fodder, labour-intensive, and permanent crops whereas time did not reveal any effect for cereal and oilseeds and pulses yields (Figure SI IV-3).

Compared to yields, we found fewer variables to be significant for explaining nitrogen application rates. For cereal, fodder, industrial, and permanent crops, significant variables were climatic, soil, and micro-economic conditions. Farm characteristics, micro-economic and climatic conditions, and accessibility were important for labour-intensive crops, while nitrogen application rates for oilseeds and pulses were dominantly explained by farm characteristics as well as micro-economic and soil conditions. Across all crop-type groups, five explanatory variables were significantly related to nitrogen application in at least half of the models (Table IV-2 and Figure IV-4).

Larger fields (field_size) were generally positively related to nitrogen application rates, except for permanent crops. Higher crop specialisation (croparea_arable) was positively related to nitrogen application rates especially for labour-intensive crops and oilseeds and pulses, but also to industrial and cereal crops. Farm economic performance (fnv_awu) had a consistently positive effect on nitrogen application, except for permanent crops. Growing degree days (gdd) revealed no uniform effect, affecting nitrogen application rates for labour-intensive crops positively, but negatively for cereal and permanent crops. Soil organic carbon content (soc_topsoil_tc) was a significantly positive related to nitrogen application for four crop-type groups (cereal, fodder, and permanent crops as well as oilseeds and pulses). Higher soil water availability (swap) was generally related to higher nitrogen application rates, especially for cereal, fodder, and industrial crops.

Predicted nitrogen application rate margins were consistently lowest for fodder and permanent crops and highest for cereal, industrial, and labour-intensive crops. Absolute variability for predicted nitrogen application margins varied strongly according to the explanatory variable and crop-type group. Country-specific effects on nitrogen application rates revealed distinct patterns for each crop-type group (Figure SI IV-4). High values were predicted for permanent crops (esp. Denmark, Finland, the Netherlands), labour-intensive crops (esp. Denmark, Ireland, the Netherlands), and industrial crops (esp. the Netherlands).

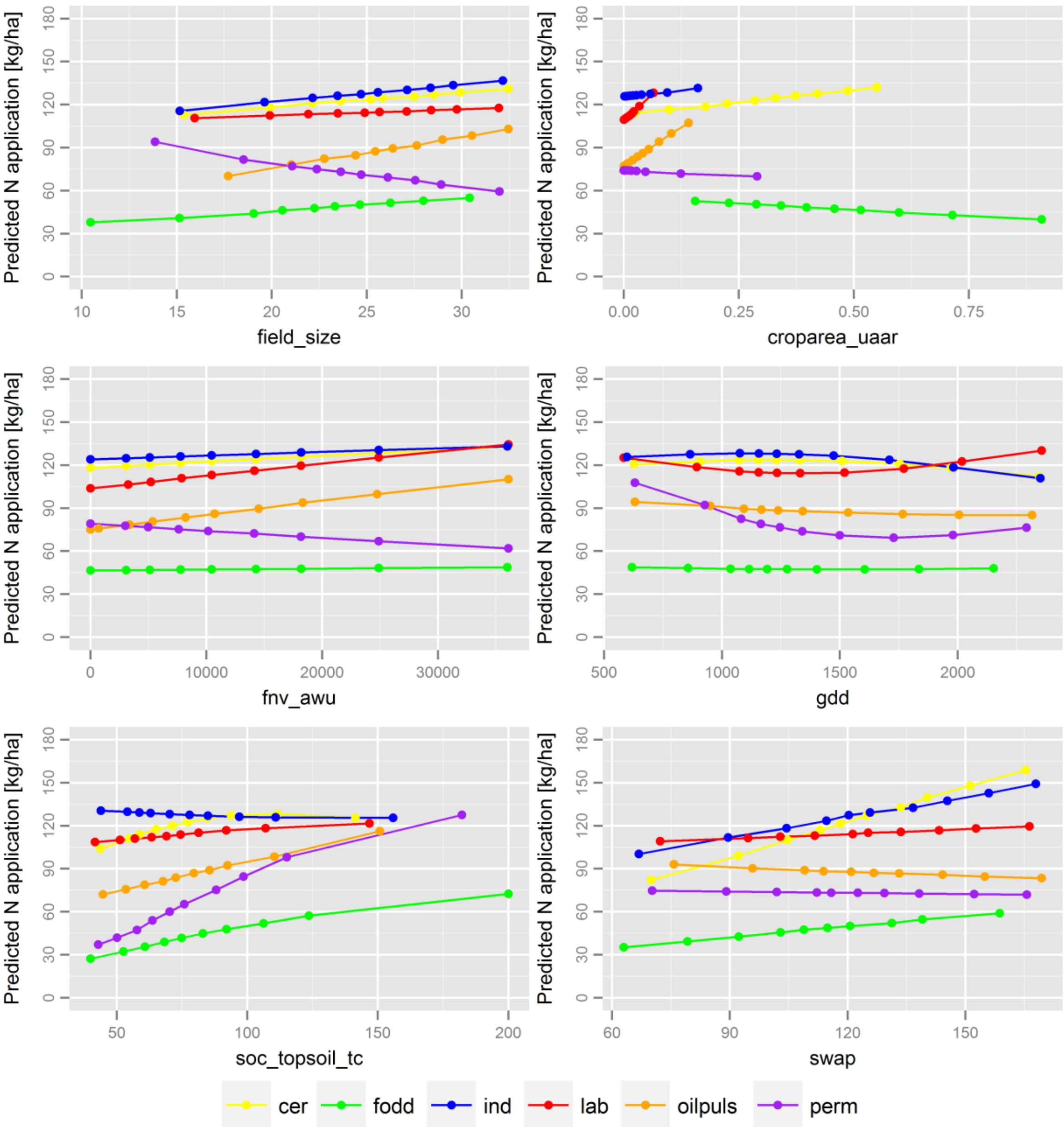

Figure IV-4: Predicted margin plots for mineral nitrogen application [kg ha^{-1}] across all six crop-type groups for the most important explanatory variables. Variables were: field size, crop-area per utilised agricultural area, economic performance, growing degree days, soil organic carbon, and soil water availability (economic performance was included).

4 Discussion

Shifting to sustainable agriculture in light of the growing demands for agricultural products is a grand challenge. Better understanding where and why agricultural intensity patterns change is important for identifying trade-offs between agriculture and the environment as well as regions and policy tools for sustainable intensification. We mapped sub-national changes in yields and nitrogen application for six broad crop-type groups across the European Union between 1990 and 2007, and used these intensity metrics to quantify the most important spatial determinants of agricultural intensity patterns and changes therein. Five main conclusions arise from our analyses, which we discuss in the following sections in more detail:

1. Crop yields increased across Europe in our study period, however with diverging trends among crop-type groups. These differences are likely the result of changes in agricultural policies, commodity prices, as well as climate change.
2. Nitrogen application rates decreased over much of Europe, explained by changes in policies (e.g., Nitrate Directive), the breakdown of socialism, and changes in nitrogen use efficiency.
3. Regions of high input and output intensity were similar across crop-type groups, and mainly located in Western and Central Europe. Lower intensity prevailed in Eastern Europe, likely as a result of the legacies from the breakdown of socialism.
4. Diverging EU-wide yield and nitrogen application trends suggest a decoupling of output from input intensity, and thus increasing nitrogen use efficiency, related to improvements in land-management.
5. Temperature was negatively related to crop yields, likely explained by our focus on the actual area under each crop-type group and suggesting that GDD increases would not increase suitability of agricultural areas under management.

4.1 Patterns and trends of agricultural-intensity change

Generally, crop yields increased modestly during our study period, in line with the documented levelling off of cropland productivity in Europe towards the late 20th century (Gingrich et al. 2015). According to our analyses, yields from cereals and oilseeds and pulses remained stagnant in the EU27 since the early to mid-1990s, while industrial and labour-intensive crop yields increased strongly in this period. Three factors explain these trends. First, agricultural policy changes, especially stricter EU-wide and national environmental protection since the early 1990s (e.g., through agri-environment schemes and cross-compliance) and the decoupling of Common Agricultural Policy (CAP) subsidies from agricultural production, likely translated into stagnating or declining cereal production (Balkhausen et al. 2008, Schmid and Sinabell 2007). Second, long-term warming negatively affected yields for wheat and barley (i.e., cereal crops), but allowed for yield increases for sugar beet (i.e., industrial crops) in Europe (Moore and Lobell 2015). Finally, biophysical limits to yields are likely approached in Europe (i.e., the potential yield, determined by soil type, climate, crop properties, and available water, is attained; Penning de Vries et al. 1995) (Peltonen-Sainio et al. 2015, Moore and Lobell 2015).

The overall decrease in mineral nitrogen application rates we found for the majority of EU27 countries is, also quantitatively, in line with other findings, as are the increasing or recovering trends we found for some countries (e.g., in the Czech Republic or Poland (EC 2015a, Sutton et al. 2011). In Western Europe (i.e., EU15), the decrease we found is likely the result of the Nitrates Directive of the European Commission in 1991 (Council of the European Union 1991) as well as the implementation of national agri-environment programmes (Peltonen-Sainio et al. 2015) that aimed at lowering nitrate pollution of water bodies. In Eastern Europe, in contrast, the institutional and economic transition following the breakdown of socialism (EC 2015a) resulted in lower support for farming in many areas, translating into increasing fertiliser prices, which led to a substantial decline in capital-intensive farming practices (Rozelle and Swinnen 2004). Nitrogen use efficiency increased in the European countries within our study period (Lassaletta et al. 2014), which fits to the observed decreases in nitrogen application we found.

Our analyses revealed a strong east-west divide in the spatial patterns of agricultural intensity in Europe (Figure IV-2). The concentration of high-intensity agricultural systems in Western/Central Europe, in contrast to mostly low-intensity systems in the peripheries of the EU27, confirms findings for yields from cereals, oilseeds and pulses, and industrial crops (Supit et al. 2010) and for nitrogen application on arable land (Temme and Verburg 2011, Overmars et al. 2014). This pattern may represent land-use legacies as Western/Central European agriculture shifted to regions with higher potential productivity in the last century (Bakker et al. 2011). These productive agricultural regions are characterised by an early industrialisation of agricultural land use and a quick adoption of technologies (Jepsen et al. 2015) as well as lower yield gaps (Neumann et al. 2010), while marginal areas experienced low-intensity land-use or even de-intensification (Kuemmerle et al. 2015, Meyfroidt and Lambin 2011). Furthermore, structural changes in agriculture and the economic challenges agricultural enterprises faced in the early post-socialist period, have led to drastic declines in harvested areas and yields in many former Socialist countries (Rozelle and Swinnen 2004), further explaining the east-west divide we observed.

Our results suggest by and large increasing yields and decreasing nitrogen application rates for the EU27 over the last almost 20 years, thus implying a decoupling of yields from nitrogen input. As European environmental policies and regulations resulted in a reduction of total nitrogen inputs to agriculture (van Grinsven et al. 2012, Jepsen et al. 2015), our study suggests yields increased significantly due to a better nitrogen management (Lassaletta et al. 2014). Another explanation for the divergent yield and nitrogen application trends might be the polarisation of land uses (i.e., concentration of agricultural production in fertile areas via intensification while marginal areas are abandoned) that resulted in production increasingly being carried out by large-scale, market-oriented farms with likely more efficient nitrogen application (Jepsen et al. 2015).

4.2 Spatial determinants of agricultural-intensity change

The strong positive influence of mineral nitrogen application on yields across all crop-type groups is not surprising as mineral nitrogen is an essential nutrient for crop growth and often the limiting factor for yields (Lobell 2007). Interestingly, the relationship between nitrogen application and yields from oilseeds and pulses was significantly negative. Contrary to prior findings for yields of selected cereal and industrial crops (Reidsma et al. 2007), temperature was negatively related to crop yields in our analysis. A possible explanation is country- and time-related differences that were explicitly included in our analysis, which controlled for temporal and latitudinal climate differences that drive yield pattern (higher yields in temperate zones compared to drier and warmer Southern and moister and colder Northern parts of Europe). Furthermore, we focussed on the actual area under each crop-type group, thus avoiding bias where aggregation units are environmentally diverse but include only a small area of agriculture (e.g. in mountain areas). This can explain the, on first sight, surprising result of a negative sign for GDD, as our models did not explain agricultural conditions in contrast to non-agricultural sites (where a positive sign can be expected at the European scale), but focussed on agricultural areas only. Given Europe's long land-use history and the concentration of agriculture on productive sites since the 19th century (Jepsen et al. 2015), most agricultural areas under management can be assumed to be in favourable conditions, and further GDD increases would thus not increase suitability and consequently crop production and yields. The positive relationship between yields and higher water availability for plants we found (both regarding precipitation and soil water content) is intuitive, as soil water availability positively affects nitrogen fertilisation and thus plant growth (Morell et al. 2011). Finally, higher farm economic performance (net value added per annual working unit) being positively related to yields indicates that higher income provides a higher capital stock that translates into higher yields due to increased intermediate consumption to improve production (e.g., through fertilisers, plant protection, high-yielding crop varieties, or mechanisation) (Alston and Pardey 2014).

We found higher nitrogen application rates where soil organic carbon contents were high. Low soil carbon-to-nitrogen ratios (C/N < 25) are preferable for nitrogen uptake, since mineralisation leads to excess nitrogen in the soil that can be taken up by plants (Chapin III et al. 2012). Also, soil water availability is positively related to nitrogen application (Abreu et al. 1993). Locations with higher economic performance had higher nitrogen application rates since farms in such regions likely have more purchase power to afford buying fertiliser (Alston and Pardey 2014). Population density played a minor role in explaining yield and nitrogen trends, in line with case-study evidence suggesting a growing disconnect of population trends and agricultural development due to urbanisation and the globalisation of agricultural markets (van Vliet et al. 2015a, Meyfroidt et al. 2013).

4.3 Model performance and uncertainties

Our panel regression approach to explain the variation in yields and nitrogen application levels resulted in a plausible variable selection and response curves, and high models fits. Nevertheless, some uncertainty remains. First, data constraints arguably influenced model performance. For example, due to the low temporal resolution of some variables, we had to limit the analyses to fairly coarse time steps that may have masked year-to-year fluctuations in yields or nitrogen application rates, although we were mainly interested in long-term trends, not yearly fluctuations. Another data constraint was that some variables had to be omitted because they did not cover our entire study area or study period (e.g., irrigation). However, we compared models with and without these variables for a subset of the data and found no major differences in sign and loading of the remaining explanatory variables. Furthermore, we did not incorporate changes in soil organic carbon or water contents due to a lack of data, although they may influence fertiliser application and hence crop yields.

Second, by considering multiple crop varieties and categorising them into crop-type groups of similar characteristics, we incorporated more information compared to assessing single crop varieties. However, this came at the expense of identifying crop-specific phenomena. Finally, other indicators exist that capture aspecst of management intensity in agricultural areas (e.g., phosphorus or pesticide application, number of tractors, or livestock density; Kuemmerle et al. 2013), which would provide a richer picture of the intensity of agricultural systems, but data on these metrics are lacking or, if existent, have strong spatial or temporal limitations (e.g., Tóth et al. 2014 for phosphorus application).

5 Conclusion

Better understanding the spatial patterns and drivers of agricultural intensity changes is an important prerequisite for designing policy tools for shifting to sustainable agriculture. A number of key insights and management implications arise from our study.

First, although yields were strongly related to nitrogen application, predicted yield margins suggested that higher nitrogen input did not result in substantial yield increases (cf. Lassaletta et al. 2014). Effects of agri-environmental policies and better nitrogen management have led to decreasing nitrogen application rates, explaining the observed decoupling of agricultural outputs from inputs due to increased nitrogen use efficiency (Lassaletta et al. 2014). Due to diminishing returns of fertiliser application (Tilman et al. 2002) and negative environmental effects of nitrogen fertilisation, such as nitrate leaching or impact on global warming potential (Erisman et al. 2011), further agricultural intensification by means of increasing nitrogen usage is unlikely in Europe.

Second, as soil quality (carbon and water content) is an important indicator for agricultural intensity, soil degradation could harm future production (Tilman et al. 2002) and possibly lead to declining agricultural intensity. Third, micro-economic settings were generally influential in explaining agricultural intensity patterns. Better micro-economic settings support higher agricultural intensity as profitable farms generally exhibit a higher level of intensity. Whereas biophysical factors typically respond rather slowly to interventions, micro-economic conditions can be affected quickly by policies, such as rural development policy of the European Union (CAP Pillar II), providing entry points for policy making.

Fourth, our results highlight the benefits of jointly analysing input and output intensity since focussing only on a single intensity metric may lead to misjudgements in regard to an agricultural system's intensity. Furthermore, our study underpins the potential of panel regression models to investigate land-use change phenomena and the power of margins plots to communicate these results

Finally, our analyses provide starting points for spatially targeted policy measures as they can help to identify candidate regions for intensification or dis-intensification or to evaluate potential benefits and trade-offs of specific land-use strategies. To attain further yield increases, policy makers may focus on intensifying agricultural areas in regions of low- to medium-intensive land use, especially in Eastern Europe, but this is challenging given the substantial conservation values that some of these landscapes have (Kleijn et al. 2009, Bignal and McCracken 1996). High-yielding agricultural areas that are characterised by both high input and output intensity could be target areas for putting efforts on increasing nitrogen use efficiency without substantially compromising yields. Generally, the implementation of agro-ecologic, biodynamic, organic, or integrated farming systems and the minimisation of farming practices that compromise sustainability goals (RISE 2014) may offer opportunities for sustainably intensifying agricultural areas in Europe.

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Supplementary Information

Table SI IV-1: Level of detail of target variables, spatial extent of all and individual crop type groups, and share of each crop type group in the total. Values were calculated as means for all and individual countries within our study region over the study period 1990-2007 (s.d. in parentheses). Relative values were derived from mean values. Values for Luxembourg included in the statistics for Belgium (asterisk).

Countries	Level of detail	Total crops	Cereals	
		1000 ha	*1000 ha*	*% of total*
Austria (AT)	NUTS2	3,121.27 (85.30)	830.35 (46.91)	26.60
Belgium (BE)*	NUTS2	1,442.91 (12.87)	339.27 (13.42)	23.51
Bulgaria (BG)	NUTS2	4,834.24 (332.74)	1,850.74 (195.19)	38.28
Czech Republic (CZ)	NUTS2	3,797.91 (171.94)	1,574.65 (54.28)	41.46
Germany (DE)	NUTS2	16,310.11 (294.04)	6,686.48 (254.23)	41.00
Denmark (DK)	NUTS0	2,544.01 (97.79)	1,434.09 (47.58)	56.37
Estonia (EE)	NUTS0	849.98 (37.29)	311.35 (34.06)	36.63
Spain (ES)	NUTS2	21,752.22 (527.94)	6,554.80 (310.30)	30.13
Finland (FI)	NUTS2	2,053.15 (67.70)	1,135.96 (102.12)	55.33
France (FR)	NUTS2	27,843.96 (574.10)	8,888.53 (336.99)	31.92
Greece (GR)	NUTS2	3,991.84 (99.61)	1,193.97 (94.97)	29.91
Hungary (HU)	NUTS2	5,216.87 (228.22)	2,753.81 (66.23)	52.79
Ireland (IR)	NUTS2	4,114.20 (171.44)	289.36 (14.42)	7.03
Italy (IT)	NUTS2	14,021.02 (564.53)	4,050.94 (117.24)	28.89
Lithuania (LT)	NUTS0	2,774.85 (147.74)	1,061.24 (105.18)	38.24
Latvia (LV)	NUTS0	1,821.13 (131.87)	512.36 (98.28)	28.13
Netherlands (NL)	NUTS2	1,928.87 (32.67)	210.39 (14.38)	10.91
Poland (PL)	NUTS2	15,756.41 (900.67)	8,308.35 (238.51)	52.73
Portugal (PT)	NUTS2	3,043.36 (101.14)	571.31 (156.97)	18.77
Romania (RO)	NUTS2	13,346.03 (410.32)	5,761.03 (432.02)	43.17
Sweden (SE)	NUTS2	2,905.29 (76.22)	1,202.16 (121.72)	41.38
Slovenia (SI)	NUTS0	511.67 (24.28)	103.91 (7.40)	20.31
Slovakia (SK)	NUTS2	2,180.32 (134.99)	816.47 (25.15)	37.45
United Kingdom (UK)	NUTS1	15,775.84 (318.77)	3,237.77 (241.09)	20.52
EU		171,937.46 (4,427.16)	59,679.31 (1,434.62)	34.71

Countries	Fodder crops		Industrial crops	
	1000 ha	*% of total*	*1000 ha*	*% of total*
Austria (AT)	2,002.03 (27.51)	64.14	76.23 (8.61)	2.44
Belgium (BE)*	859.10 (17.53)	59.54	170.79 (9.36)	11.84
Bulgaria (BG)	2,015.08 (259.72)	41.68	88.14 (24.52)	1.82
Czech Republic (CZ)	1,700.14 (164.21)	44.77	163.73 (47.20)	4.31
Germany (DE)	7,198.12 (342.42)	44.13	866.63 (135.29)	5.31
Denmark (DK)	796.05 (44.27)	31.29	92.27 (10.21)	3.63
Estonia (EE)	473.96 (17.49)	55.76	28.13 (11.75)	3.31
Spain (ES)	8,772.26 (176.35)	40.33	377.99 (90.66)	1.74
Finland (FI)	744.08 (57.97)	36.24	74.66 (9.45)	3.64
France (FR)	14,488.08 (353.22)	52.03	690.14 (19.91)	2.48
Greece (GR)	1,378.97 (84.88)	34.54	401.83 (56.65)	10.07
Hungary (HU)	1,469.60 (208.19)	28.17	125.88 (45.82)	2.41
Ireland (IR)	3,762.75 (155.10)	91.46	45.83 (14.56)	1.11
Italy (IT)	6,263.80 (199.08)	44.67	316.85 (73.50)	2.26
Lithuania (LT)	1,439.08 (135.24)	51.86	140.21 (33.02)	5.05

Latvia (LV)	1,179.95 (77.53)	64.79	77.89 (19.56)	4.28
Netherlands (NL)	1,312.97 (30.79)	68.07	283.46 (23.86)	14.70
Poland (PL)	4,910.35 (680.60)	31.16	1,476.10 (458.27)	9.37
Portugal (PT)	1,561.58 (284.41)	51.31	75.05 (22.24)	2.47
Romania (RO)	5,606.34 (235.66)	42.01	360.55 (65.68)	2.70
Sweden (SE)	1,462.27 (99.58)	50.33	101.42 (12.87)	3.49
Slovenia (SI)	365.85 (17.53)	71.50	14.97 (3.14)	2.93
Slovakia (SK)	1,058.66 (131.15)	48.56	70.60 (22.70)	3.24
United Kingdom (UK)	11,351.22 (300.67)	71.95	350.04 (44.35)	2.22
EU	82,172.30 (2,705.03)	47.79	6,469.40 (1,064.02)	3.76

Countries	**Labour-intensive crops**		**Oilseeds and pulses**		**Permanent crops**	
	1000 ha	*% of total*	*1000 ha*	*% of total*	*1000 ha*	*% of total*
Austria (AT)	12.55 (2.11)	0.40	24.53 (55.07)	4.65	55.07 (2.94)	1.76
Belgium (BE)*	52.53 (3.99)	3.64	2.43 (8.00)	0.91	8.00 (0.75)	0.55
Bulgaria (BG)	143.94 (54.98)	2.98	122.44 (162.58)	11.87	162.58 (17.71)	3.36
Czech Republic (CZ)	28.94 (9.88)	0.76	74.55 (12.18)	8.38	12.18 (5.82)	0.32
Germany (DE)	102.53 (15.61)	0.63	265.02 (167.00)	7.91	167.00 (8.45)	1.02
Denmark (DK)	12.64 (2.45)	0.50	84.11 (7.62)	7.91	7.62 (0.66)	0.30
Estonia (EE)	3.59 (0.74)	0.42	28.91 (2.70)	3.56	2.70 (0.75)	0.32
Spain (ES)	414.97 (46.35)	1.91	302.15 (4,253.95)	6.34	4,253.95 (110.98)	19.56
Finland (FI)	9.55 (1.87)	0.47	10.28 (6.07)	4.03	6.07 (0.58)	0.30
France (FR)	309.37 (28.33)	1.11	143.12 (1,040.48)	8.72	1,040.48 (32.21)	3.74
Greece (GR)	175.21 (20.43)	4.39	10.80 (807.51)	0.86	807.51 (67.65)	20.23
Hungary (HU)	107.73 (15.73)	2.07	91.45 (156.95)	11.56	156.95 (20.43)	3.01
Ireland (IR)	6.98 (0.41)	0.17	2.37 (1.50)	0.19	1.50 (0.62)	0.04
Italy (IT)	537.65 (40.54)	3.83	172.67 (2,345.23)	3.61	2,345.23 (139.22)	16.73
Lithuania (LT)	24.67 (8.43)	0.89	63.18 (8.80)	3.63	8.80 (4.04)	0.32
Latvia (LV)	13.92 (3.54)	0.76	37.24 (6.40)	1.68	6.40 (3.14)	0.35
Netherlands (NL)	98.79 (9.08)	5.12	7.53 (14.79)	0.44	14.79 (2.15)	0.77
Poland (PL)	246.71 (36.48)	1.57	181.61 (186.62)	3.99	186.62 (21.73)	1.18
Portugal (PT)	53.68 (13.41)	1.76	72.09 (678.37)	3.40	678.37 (25.16)	22.29
Romania (RO)	247.83 (47.34)	1.86	278.20 (327.37)	7.81	327.37 (24.35)	2.45
Sweden (SE)	9.67 (5.03)	0.33	50.83 (3.13)	4.36	3.13 (0.81)	0.11
Slovenia (SI)	3.16 (0.56)	0.62	1.86 (20.79)	0.59	20.79 (2.31)	4.06
Slovakia (SK)	29.25 (15.31)	1.34	44.90 (24.09)	8.31	24.09 (3.44)	1.10
United Kingdom (UK)	141.80 (20.65)	0.9	75.33 (24.82)	4.25	24.82 (5.12)	0.16
EU	2,787.68 (252.47)	1.62	524.38 (10,322.02)	6.11	10,322.02 (61.01)	6.00

Table SI IV-2: Correlation matrix of explanatory variables. Spearman ρ values were calculated for each year and each crop-type group resulting in 48 correlation matrices. For the sake of brevity, mean Spearman ρ values across all time steps and crop-type groups were displayed and marked as bold if ρ exceeded 0.7.

VARIABLE	nitrogen appl.	field_size	sgm	holdings _uaar	croparea _uaar	fert _uaar	fnv _awu	acc50	rugg	soil_pH	soc_top-soil_tc	swap	gdd	prcp_ sum_year	pop
nitrogen appl.	1.00	0.43	0.22	0.60	0.46	0.67	0.66	0.09	0.61	0.47	0.35	0.67	0.35	0.11	0.06
field_size		1.00	0.18	0.50	0.44	0.58	0.57	0.12	0.37	0.19	0.26	0.35	0.19	0.09	0.03
sgm			1.00	0.06	0.04	0.41	0.21	0.13	0.54	0.01	0.17	0.45	0.30	0.24	0.25
holdings_uaar				1.00	**0.73**	0.50	**0.80**	0.31	0.39	0.69	0.60	0.53	0.68	0.27	0.49
croparea_uaar					1.00	0.56	0.52	0.14	0.41	**0.72**	0.70	0.45	0.67	0.28	0.36
fert_ uaar						1.00	**0.76**	0.07	0.62	0.45	0.47	0.68	0.34	0.11	0.11
fnv_awu							1.00	0.26	0.46	0.57	0.44	0.60	0.52	0.14	0.23
acc50								1.00	0.33	0.14	0.03	0.20	0.23	0.03	**0.71**
rugg									1.00	0.45	0.18	0.63	0.06	0.09	0.22
soil_pH										1.00	0.64	0.39	0.66	0.39	0.32
soc_topsoil_tc											1.00	0.37	0.61	0.46	0.20
swap												1.00	0.16	0.13	0.09
gdd													1.00	0.45	0.27
prcp_sum_year														1.00	0.13
pop															1.00

Table SI IV-3: Regression results for yields for six crop-type groups. Asterisks indicate statistical significance at the 10% (*), 5% (**), and 1% (***) level. Finland was excluded in the country dummy calculation to prevent perfect collinearity. NUTS regions for Belgium, Slovenia, and Spain had to be excluded due to data gaps in the explanatory variable set.

VARIABLE	**CER**		**FODD**		**IND**	
	coeff	*robust s.e.*	*coeff*	*robust s.e.*	*coeff*	*robust s.e.*
Sweden	563.1	342.5	**27,656*** **	4369	2295	3551
Estonia	**-1,026** **	416.5	**30,774*** **	6252	**-13,504*** **	3305
Latvia	-580.4	539	**31,726*** **	7825	**-16,640*** **	3989
Lithuania	-765.8	612.8	**29,150*** **	6908	**-17,621*** **	4981
Denmark	897.3	591.5	**52,140*** **	8632	**15,244** **	7340
United Kingdom	**979.2** **	450.3	**33,123*** **	6610	**6,940* **	3901
Ireland	**2,400*** **	535.1	**25,961*** **	5788	**6,066* **	3583
Poland	-894.9	577.6	**21,391*** **	5178	-3925	3956
Netherlands	**890.9* **	485.9	**19,869*** **	6102	6402	4409
Germany	**885.6* **	475.9	**27,599*** **	4414	1832	4192
Czech Republic	-313.7	553.6	**28,573*** **	5487	-3920	4984
Luxemburg	140.4	426.4	7739	6063	**-15,196*** **	3705
Slovakia	-610.3	595.6	**30,403*** **	6062	-8890	6134
Austria	**1,856** **	881	**35,595*** **	6901	4332	6137
Hungary	370.4	650.5	**24,043*** **	6267	1528	5140
France	**1,266** **	531.1	**28,793*** **	5825	727.3	5407
Italy	**1,494** **	746.3	**29,503*** **	6634	**11,889** **	5567
Portugal	**1,705** **	832	**29,573*** **	7351	**16,506** **	6617
Greece	**1,207* **	641.6	**25,159*** **	6946	-1050	5575
Time step 2	**342.6*** **	116.6	**9,048*** **	2101	**-2,464*** **	932.9
Time step 3	**253.9** **	106	**5,673*** **	2032	-1174	1125
Time step 4	**646.0*** **	116.4	**6,926*** **	2122	911.9	1199
Time step 5	**771.5*** **	112.2	**11,227*** **	2423	**2,803** **	1289
Time step 6	**501.5*** **	127.4	**9,395*** **	2487	1451	1243
Time step 7	**983.9*** **	135.9	**9,564*** **	2379	**5,178*** **	1342
Time step 8	**694.7*** **	153.4	**6,696*** **	2162	**4,284*** **	1439
fert_uaar	**1.711** **	0.742	**322.7*** **	44.54	0.583	7.488
fnv_awu	**0.00871* **	0.00494	-0.193	0.121	0.0477	0.0673
nitrogen appl.	**10.50*** **	2.113	**136.7*** **	49.6	**66.09*** **	8.018
acc50	**-13.94*** **	4.57	12.41	34.26	17.77	32.68
acc50²	**0.0416** **	0.019	-0.0637	0.118	0.0788	0.142
prcp_sum_year	0.276	0.179	-4.503	2.936	**4.659*** **	1.545
prcp_sum_year²	**-0.000437* **	0.000243	0.0045	0.00314	-0.00202	0.00159
fieldsize	-13.11	16.1	107.5	205.4	**539.5*** **	156.2
soil pH	**-404.8*** **	134.3	-2304	1926	1563	1385
soc_topsoil_tc	-1.198	5.663	**101.8** **	43.2	-74.98	52.34
soc_topsoil_tc²	-0.0969	0.0744	-0.26	0.159	0.175	0.557
rugg	**-11.38*** **	4.21	1.804	34.77	-2.247	31.08
gdd	**-0.791*** **	0.216	-1.933	2.418	**-4.671*** **	0.937
gdd²	**-0.000542*** **	0.000191	0.000263	0.00234	**-0.00742*** **	0.00134
sgm	0.000253	0.000161	**-0.00679*** **	0.00212	0.000298	0.0019
popdens	0.4	1.09	-13.4	12.48	**15.51* **	9.058
popdens²	-0.000805	0.0013	-0.0218	0.02	-0.00894	0.0114
holdings_uaar	-878.6	2019	**28,957* **	16340	**-35,450*** **	8039
croparea_uaar	-122.7	566.5	-11506	7541	-3996	9877
swap	**10.85*** **	3.727	-21.91	50.91	**144.6*** **	35.72
Constant	**3,875*** **	885	-18410	18463	**-14,583* **	8582

VARIABLE	LAB		OIL		PERM	
	coeff	*robust s.e.*	*coeff*	*robust s.e.*	*coeff*	*robust s.e.*
Sweden	**12,204*** **	2318	**932.4*** **	230.5	**15,957*** **	5739
Estonia	-3762	2701	25.17	242.9	8209	7446
Latvia	**-14,390*** **	3419	49.33	265.2	**14,549***	7506
Lithuania	**-13,696*** **	4122	345.6	299.1	**13,536** **	6255
Denmark	-1274	4096	**1,572*** **	342.8	**13,948** **	6587
United Kingdom	**-12,269*** **	2275	**1,469*** **	247.9	**42,885*** **	9259
Ireland	**-5,393***	3128	**1,561*** **	291.3	280.5	10096
Poland	-3091	3679	**1,211*** **	296.4	**15,722** **	6546
Netherlands	**17,817*** **	3361	**1,460*** **	251	**194,549*** **	7948
Germany	**10,016*** **	3012	**1,488*** **	263.5	**30,345*** **	6269
Czech Republic	**-10,933*** **	3336	**917.8*** **	286.9	**34,456*** **	6726
Luxemburg	2637	2379	**2,088*** **	243.2	**19,600*** **	6012
Slovakia	**-14,705*** **	4664	314.3	303.8	**22,949*** **	7465
Austria	**23,724*** **	4629	**1,336*** **	316.7	**36,606*** **	7731
Hungary	-6172	4291	**670.4** **	340.8	**21,468*** **	7245
France	**-5,191***	3139	**1,657*** **	299.2	**24,663*** **	7003
Italy	-4204	5332	**1,707*** **	385.6	**23,216*** **	8425
Portugal	3676	4512	-72.87	380	**22,764*** **	7672
Greece	-612.4	5651	**1,431*** **	391.7	**28,568*** **	7624
Time step 2	-1793	1286	58.26	60.91	-635.7	453.1
Time step 3	1448	1224	-26.26	77.61	**-4,495** **	1911
Time step 4	**3,421*** **	1239	**138.7** **	69.18	**2,909*** **	910.1
Time step 5	**4,614*** **	986.8	36.34	83.66	**3,368*** **	1113
Time step 6	**2,551** **	1138	-33.33	77.72	**3,268*** **	1060
Time step 7	**3,595*** **	1033	**218.3*** **	83.23	**1,737** **	879.3
Time step 8	**2,477** **	1262	54.59	83.93	897.3	1095
fert_uaar	-8.198	6.713	0.0535	0.426	1.686	4.95
fnv_awu	-0.0204	0.0674	**0.00752** **	0.00311	**-0.181** **	0.092
nitrogen appl.	**30.39*** **	10.63	**-2.029*** **	0.635	**64.90*** **	16.58
acc50	-19.18	27.55	-0.626	1.771	-36.21	40.1
$acc50^2$	0.00663	0.13	**0.0218*** **	0.00824	0.231	0.182
prcp_sum_year	2.926	1.872	0.168	0.131	**8.400*** **	2.653
prcp_sum_year²	-0.00467	0.00349	-0.000106	0.000218	0.000717	0.00456
fieldsize	-41.08	157.5	**38.06*** **	8.334	-190.7	225.9
soil pH	-1073	1563	**-112.7** **	55.53	-34.03	1350
soc_topsoil_tc	3.601	45.9	2.007	1.916	**89.74** **	41.11
soc_topsoil_tc²	-0.0127	0.245	0.0109	0.0105	-0.157	0.143
rugg	12.9	43.51	**-6.954** **	3.084	**-93.64***	50.4
gdd	**-3.961** **	1.657	**-0.291** **	0.143	**-3.882** **	1.847
gdd^2	0.00158	0.00152	**-0.000185***	0.000101	0.00241	0.00213
sgm	**0.00322*** **	0.00101	0.0000527	0.0000764	0.00108	0.00155
popdens	3.535	6.918	**1.161** **	0.502	-3.565	8.946
$popdens^2$	-0.000269	0.00822	**-0.00115***	0.000598	-0.00556	0.012
holdings_uaar	-9716	14448	-805.2	785.9	-1260	8759
croparea_uaar	**92,819*** **	34920	**2,505*** **	752.6	**-10,247***	5318
swap	**-49.39***	25.59	**4.940*** **	1.527	-31.25	48.39
Constant	**35,557*** **	7497	439.2	388.6	-4467	11575

Table SI IV-4: Regression results for applied mineral nitrogen for six crop-type groups. Asterisks indicate statistical significance at the 10% (*), 5% (**), and 1% (***) level. Finland was excluded in the country dummy calculation to prevent perfect collinearity. NUTS regions for Belgium, Slovenia, and Spain had to be excluded due to data gaps in the explanatory variable set.

VARIABLE	**CER**		**FODD**		**IND**	
	coeff	*robust s.e.*	*coeff*	*robust s.e.*	*coeff*	*robust s.e.*
Sweden	**-33.91****	13.17	-3.316	10.7	**-22.44***	13.05
Estonia	**-97.66*****	15.8	**-39.71*****	14.96	**-40.54*****	14.99
Latvia	**-132.5*****	19.07	**-53.96*****	18.44	**-39.35****	19.39
Lithuania	**-68.70*****	21	-19.21	16.79	-11.51	20.37
Denmark	-33.92	21.26	**65.26*****	17.34	-25.85	35.58
United Kingdom	7.846	16.93	-5.012	15.54	21	20.71
Ireland	-7.288	17.74	20.84	17.57	12.62	19.19
Poland	**-44.24***	23.82	-8.089	12.87	10.01	18.02
Netherlands	31.62	23.04	**55.92****	24.42	**108.8*****	22.69
Germany	-3.907	16.66	0.664	11.49	**34.12***	18.34
Czech Republic	-25.04	18.97	-13.37	13.59	1.494	21.64
Luxemburg	**-27.29***	16.12	**89.41*****	12.43	**51.84*****	18.67
Slovakia	**-77.50*****	19.18	**-29.25****	14.07	-5.389	25.75
Austria	**-76.07*****	21.35	**-35.89****	14.46	-24.34	23.05
Hungary	**-82.35*****	24.85	**-35.05****	16.01	32.96	26.26
France	-11.54	19.43	-18.62	13.9	24.16	22.56
Italy	-0.578	24.9	-6.605	17.9	**57.38***	29.93
Portugal	-8.109	19.54	5.409	17.23	39.4	27.97
Greece	-0.143	22.11	-1.249	17.28	25	30.85
Time step 2	-3.148	4.765	-1.54	2.624	2.082	6.941
Time step 3	2.495	4.283	5.219	4.891	3.721	5.974
Time step 4	-4.162	3.904	-3.194	3.856	-5.68	6.064
Time step 5	**-6.644***	4.039	**-6.981***	3.828	**-16.29*****	5.88
Time step 6	**-12.22*****	4.563	**-14.59*****	3.439	**-14.16****	6.318
Time step 7	**-12.97*****	4.658	**-18.40*****	3.432	**-18.72*****	6.527
Time step 8	**-14.98*****	5.02	**-20.16*****	3.475	**-23.26*****	6.623
fert_uaar	0.0281	0.0263	**0.149*****	0.0483	0.00273	0.0251
fnv_awu	0.000404	0.00025	0.0000578	0.000442	0.000248	0.000408
nitrogen appl.	-	-	-	-	-	-
acc50	-0.00271	0.156	-0.0751	0.0855	0.0916	0.163
acc50²	-0.000375	0.000708	0.000248	0.00027	-0.000181	0.000689
prcp_sum_year	0.00252	0.00624	**-0.00903***	0.00538	0.00655	0.00949
prcp_sum_year²	0.000000394	0.0000071	-0.00000393	0.00000436	-0.0000123	0.0000124
fieldsize	**0.980***	0.563	0.826	0.581	1.203	0.776
soil pH	-0.487	4.464	2.347	3.723	**-14.03***	7.524
soc_topsoil_tc	**0.304***	0.166	**0.313****	0.133	-0.0625	0.221
soc_topsoil_tc²	**-0.00432****	0.0017	**-0.000837****	0.000411	0.000502	0.00278
rugg	-0.0827	0.114	0.117	0.0737	-0.194	0.176
gdd	-0.00363	0.00493	-0.000726	0.00314	-0.00659	0.00664
gdd²	**-9.05e-06***	0.00000532	0.00000196	0.00000456	-0.0000109	0.00000839
sgm	-0.000000537	0.00000429	-0.00000479	0.00000353	0.00000501	0.0000084
popdens	-0.00246	0.0409	-0.0568	0.0381	-0.00982	0.0441
popdens²	0.0000257	0.0000478	0.0000555	0.0000466	0.0000314	0.0000516
holdings_uaar	36.65	94.06	-31.1	27.41	-36.81	55.08
croparea_uaar	**33.31***	20.01	-16.44	12.82	37.35	73.79
swap	**0.840*****	0.131	**0.269***	0.141	**0.483*****	0.168
Constant	7.098	30.39	-4.288	31.1	**97.36****	47.14

VARIABLE	LAB		OIL		PERM	
	coeff	*robust s.e.*	*coeff*	*robust s.e.*	*coeff*	*robust s.e.*
Sweden	14.17	13.24	-10.44	15.24	**-254.3*** **	79.53
Estonia	**-25.96** **	12.82	**-28.38* **	17.16	**-332.5*** **	81.64
Latvia	**-58.71*** **	15.84	-25.82	17.44	**-312.7*** **	82.36
Lithuania	**-46.70*** **	16.92	6.946	21.33	**-271.2*** **	82.75
Denmark	**51.70** **	22.12	**84.01*** **	24.15	-82.11	88.35
United Kingdom	-17.87	13.52	-12.57	16.16	**-186.0** **	92.25
Ireland	**81.02*** **	14.65	**37.04* **	19.62	**-390.8*** **	84.42
Poland	**-50.30*** **	15.77	**55.34** **	21.77	**-276.5*** **	83.85
Netherlands	**97.48*** **	20.18	14.67	25.09	-99.21	88.6
Germany	-4.289	14.73	**72.95*** **	20.09	**-175.0** **	88.28
Czech Republic	-23.34	14.35	**46.83** **	22.1	**-186.6** **	86.86
Luxemburg	**-44.79*** **	13.48	**92.41*** **	17.32	**-199.3** **	85.52
Slovakia	**-34.05* **	17.56	3.902	22.23	**-234.0*** **	88.23
Austria	-25.18	15.85	-1.785	23.54	**-224.7*** **	85.86
Hungary	**-69.61*** **	17.12	**37.82* **	22.96	**-258.6*** **	85.13
France	**-28.73* **	15.87	34.97	21.74	**-239.2*** **	85.8
Italy	-16.29	17.94	38.1	23.37	**-247.2*** **	88.74
Portugal	-21.35	21.35	-19.1	24.72	**-250.1*** **	89.28
Greece	**-41.54** **	17.46	30.48	24.45	**-243.7*** **	83.84
Time step 2	-3.819	6.699	3.058	6.292	-5.18	3.636
Time step 3	6.361	6.74	**23.19*** **	5.348	11.99	7.675
Time step 4	2.127	6.997	**11.26** **	4.89	7.821	6.453
Time step 5	-7.645	7.042	6.595	5.772	**-9.030* **	5.363
Time step 6	-11.42	7.332	3.355	5.93	-4.029	6.477
Time step 7	**-17.24** **	6.856	0.173	5.505	**-15.48*** **	5.78
Time step 8	**-22.59*** **	6.83	2.398	5.495	-6.891	5.609
fert_uaar	-0.00555	0.0258	0.00269	0.0187	**0.0449** **	0.0217
fnv_awu	**0.000832*** **	0.00032	**0.000948** **	0.000372	-0.000469	0.000454
nitrogen appl.	-	-	-	-	-	-
acc50	**0.249** **	0.107	0.0279	0.103	0.13	0.185
acc50²	**-0.00177*** **	0.000523	-0.0000172	0.000514	-0.00254	0.00166
prcp_sum_year	-0.00293	0.00888	-0.00274	0.00986	-0.00108	0.0121
prcp_sum_year²	-0.00000561	0.000016	-0.00000273	0.0000148	-0.0000117	0.0000168
fieldsize	0.431	0.604	**2.144*** **	0.774	**-1.605* **	0.925
soil pH	6.508	5.123	-4.603	4.009	3.981	6.156
soc_topsoil_tc	0.128	0.135	**0.372** **	0.15	**0.721*** **	0.219
soc_topsoil_tc²	-0.00041	0.00076	0.000108	0.000726	**-0.00157** **	0.000709
rugg	0.0548	0.134	0.0699	0.204	-0.279	0.183
gdd	0.00138	0.00662	-0.00589	0.00913	**-0.0220* **	0.0123
gdd²	**1.71e-05** **	0.00000756	0.00000352	0.00000677	**3.03e-05*** **	0.0000116
sgm	0.00000208	0.00000535	-0.000000962	0.0000056	0.0000048	0.00000534
popdens	-0.00621	0.0308	0.0308	0.0284	-0.0867	0.082
popdens²	0.0000401	0.0000358	-0.0000545	0.0000467	**0.000177* **	0.000101
holdings_uaar	**129.8*** **	47.04	-64.93	41.1	52.27	40.17
croparea_uaar	**269.1** **	105.2	**212.6*** **	62.71	-14.17	42.36
swap	0.113	0.116	-0.0987	0.12	-0.0295	0.208
Constant	47.62	32.7	11.08	30.67	**310.8*** **	97.94

Figure SI IV-1: Time series of crop yields for all countries (data for Luxembourg were included in the sub-national statistics of Belgium following CAPRI nomenclature). Y-axes depict yields [kg ha^{-1}], x-axes the years of the study period. Colour coding: all crop type groups (black), cereals crops (yellow), fodder crops (green), industrial crops (blue), labour-intensive crops (red), oilseeds and pulses (orange), and permanent crops (purple).

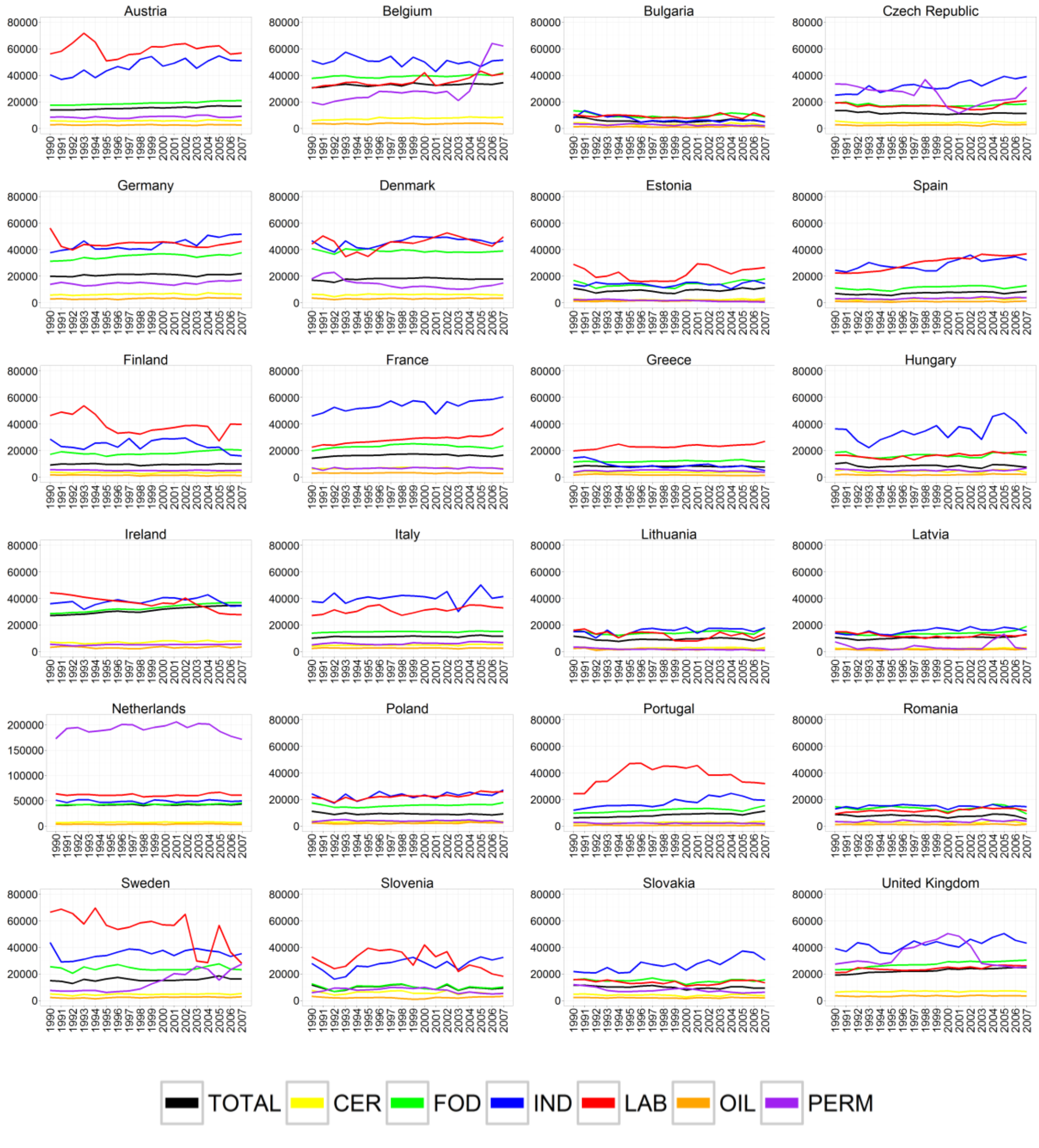


Figure SI IV-2: Time series of national mineral nitrogen application for all countries of our study region (data for Luxembourg were included in the sub-national statistics of Belgium following CAPRI nomenclature). Y-axes depict nitrogen application [kg ha^{-1}]. Colour coding: all crop type groups (black), cereals crops (yellow), fodder crops (green), industrial crops (blue), labour-intensive crops (red), oilseeds and pulses (orange), and permanent crops (purple).

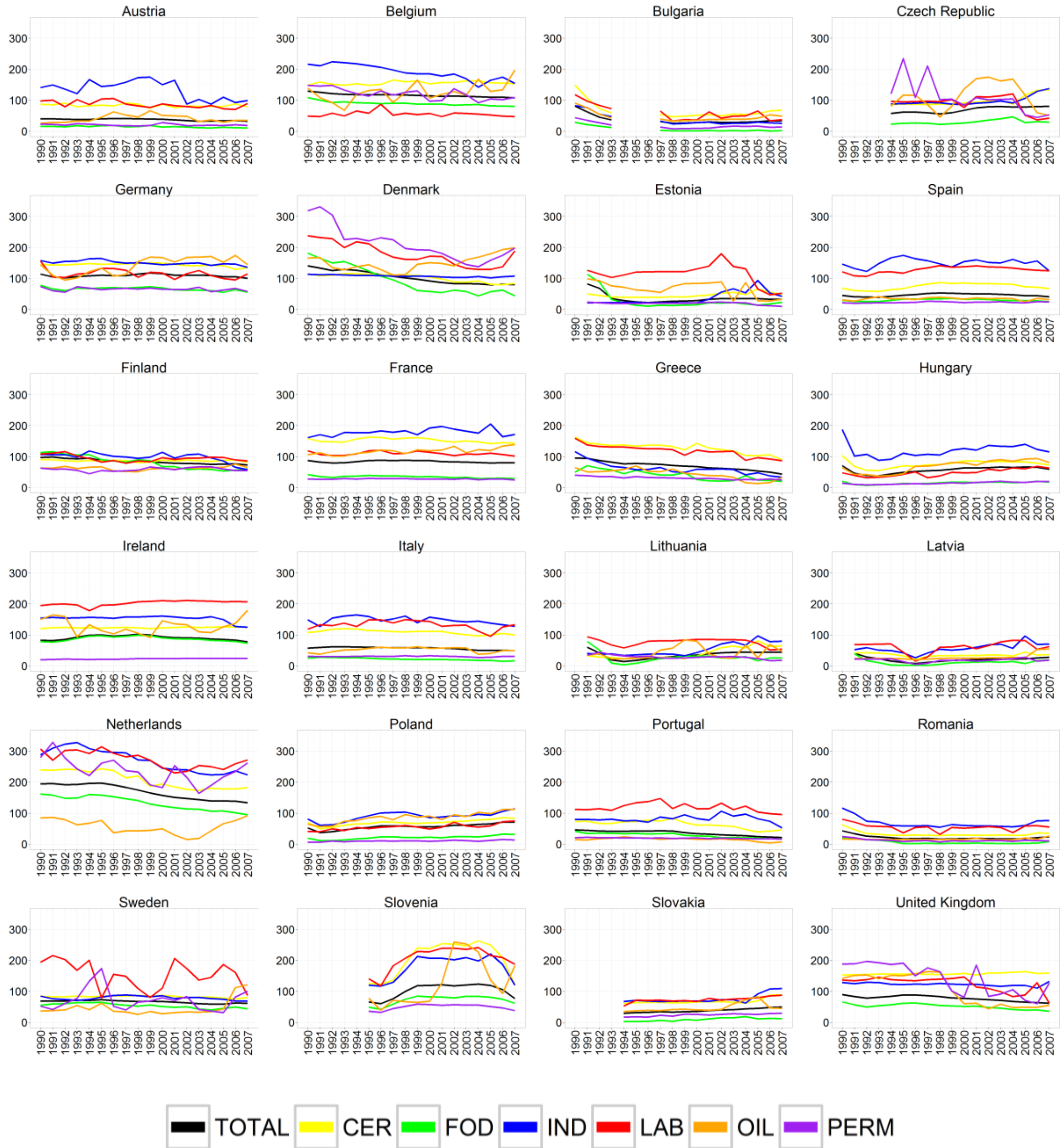


Figure SI IV-3: Predicted yield margins across all crop-type groups for country (upper panel) and time dummy (lower panel).

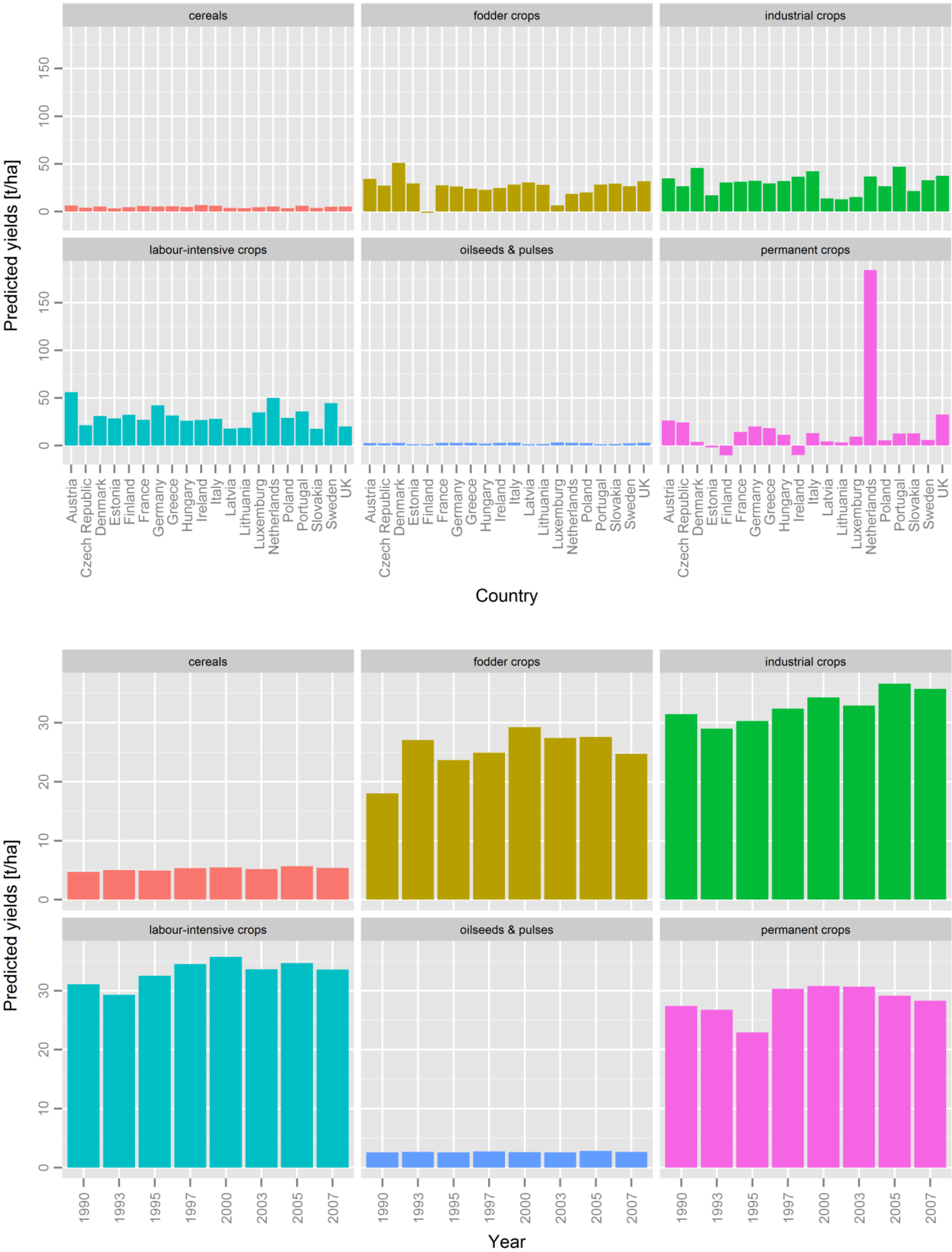
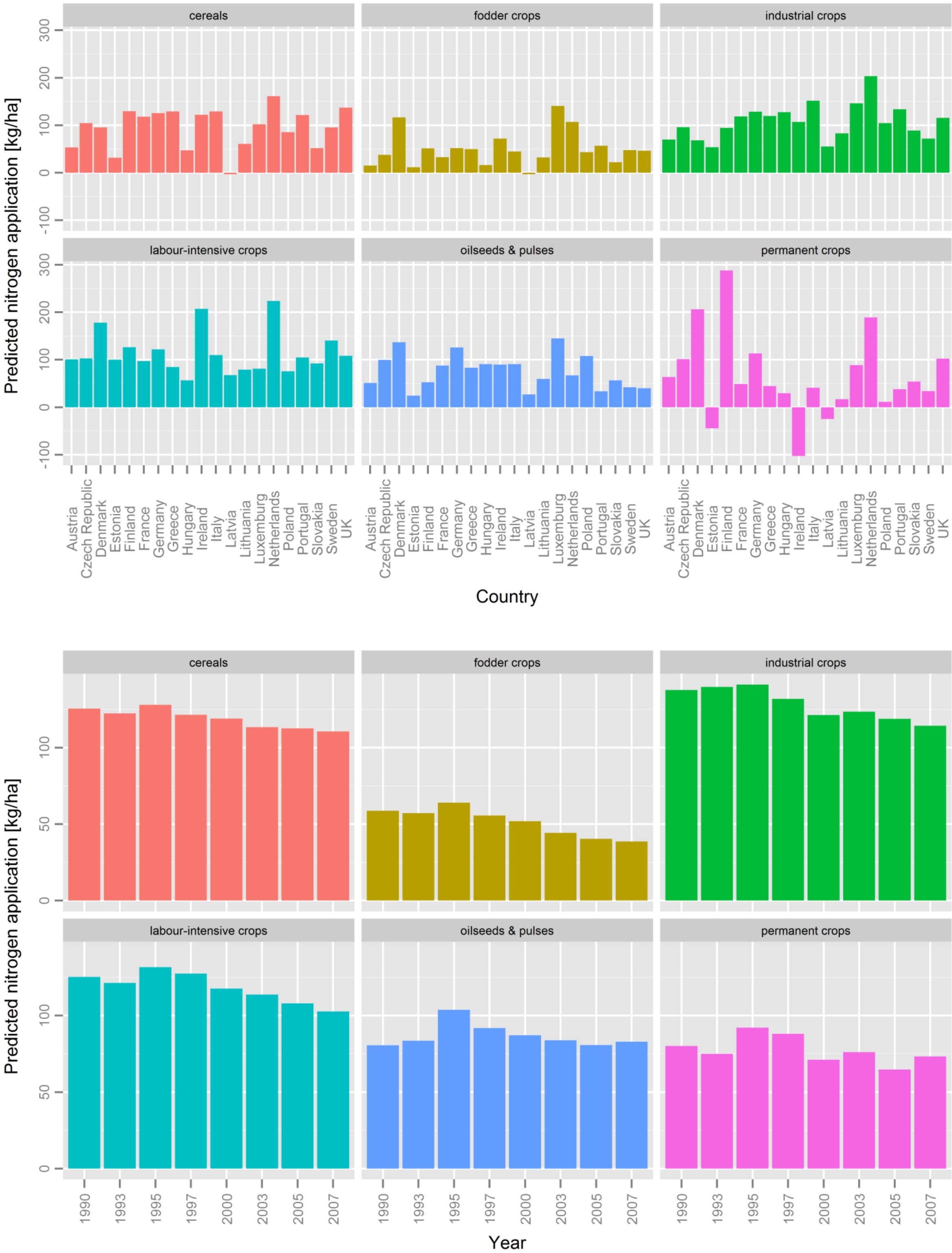


Figure SI IV-4: Predicted nitrogen application rate margins across all crop-type groups for country (upper panel) and time dummy (lower panel).



Text SI IV-1: Extended description of CAPRI data generation.

The CAPRI database used in this study builds upon EUROSTAT official statistics for the European Commission, which were gap-filled and harmonised as well as complemented by national level data sources for the recent member states (Britz and Witzke 2014). To produce a subnational level database, CAPRI uses harvested areas and yields directly from EUROSTAT while an econometric method is applied to estimate crop-type specific fertiliser inputs since regional crop-type specific fertiliser input data are not readily available in official statistics (Britz and Witzke 2014). Therefore, regional crop (harvested area, production, and yields) and animal production (livestock numbers) are used together with data on purchased mineral fertilisers (N, P_2O_5, and K_2O) per crop per member state per year from the International Fertilizer Association (IFA) and the European Fertiliser Manufacturers Association (EFMA). Gaps in time series of fertiliser inputs per crop per region per year are estimated within a Bayesian Highest Posterior Density framework that minimises the difference between a certain variable and a known and corresponding initial estimate (Britz and Witzke 2014). The variables included in this HPD framework are: (i) the share of fertiliser from animal manure per crop, (ii) the amount of 'working' fertilisers in animal manure and penalties on the differences with expert data on the application of mineral fertilisers per crop per member state from IFA, (iii) minimum amounts of fertilisers to be covered by mineral fertiliser and crop residues, (iv) total nutrient surpluses above initial estimate, and (v) total application of animal manure per arable crop above a certain amount. Among other things, the constraints included in this HPD framework ensure consistency between fertiliser supply and demand and consistency with given national and regional statistics (e.g. total use of purchased mineral fertiliser at national level). Moreover, consistency between different levels of aggregation should also be ensured. Importantly, transportation of animal manure between regions and member states is not allowed in the modelling framework why all produced manure is also applied within the same region (Britz and Witzke 2014).

Text SI IV-2: Rationale of variable selection process.

Nitrogen application

We used mineral nitrogen application rates to explain crop yields as nitrogen is an essential nutrient for crop growth and often the limiting factor for crop yields (Lobell 2007).

Farm and farmer characteristics

Field size (*fieldsize*) provides information on the spatial configuration of land use and may influence patterns of agricultural intensity as large fields can be an indicator of large-scale, intensive agri-business farming (Kuemmerle et al. 2013). Standard gross margins (*sgm*) is an economic measure to estimate the business size of an agricultural holdings (EC 2015b) while not considering its utilised agricultural nor its production intensity. The larger the business size of a holding, the more likely is high management intensity as more capital allows for more paid labour and intermediate consumption such as expenses for fertiliser or machines. Standard gross margins were strongly correlated with annual working units that correspond to the work being done by one person full-time occupied on an agricultural holding. The number of holdings per utilised agricultural area (*holdings_uaar*) can be related to agricultural intensity as a low ratio within a region may indicate a polarisation/monopolisation of agricultural use with high-intensive management on these holdings. The area coverage of a crop-type group to the total utilised agricultural area (*croparea_uaar*) represents a measure of awareness as farmers that grow crop varieties of a specific crop-type group on large areas are expected to put more effort in obtaining a high crop yields (Reidsma et al. 2007).

Micro-economy

Expenses for fertiliser (*fert_uaar*) per utilised agricultural area express the technological ability while farms with high expenses for external goods aim for high input and output intensity (Reidsma et al. 2007). Due to high collinearity with expenses for fertilisers, we refrained from using expenses for plant protection and seeds. Farm net value added per annual working unit (*fnv_awu*) relates farm output to labour input by subtracting capital used for intermediate consumption (e.g., fertiliser, plant protection, energy) and depreciation from and adding subsidies to total farm output. This indicator is a measure of farmers’ income to represent farm performance or revenues (Reidsma et al. 2007), with higher values indicating a higher degree of intensity.

Access

The travel time of a location to settlements larger 50,000 inhabitants (*acc50*), calculated following Nelson (2008), can influence agricultural intensity as market access and infrastructural networks can strongly determine land-use changes (Geist and Lambin 2002) and high-intensively managed areas can occur close to settlements (market access) or further away (possible environmental impacts). High terrain ruggedness (*rugg*) restricts the management intensity on agricultural areas due to the low suitability for large-scale, mechanised management practices and possibly higher surface runoff.

Soil

Soil pH (*soil pH*), soil organic carbon content (*soc_topsoil_tc*), and soil water availability for plants (*swap*) influence plants' ability for N uptake. Most plant nutrients are optimally availably for uptake by plants within a pH range of 6.5 to 7.5 (Jensen 2010). Low soil carbon-to-nitrogen ratios (C/N < 25) are preferable for the nitrogen uptake by plants since net N mineralisation occurs that leads to excess N in the soil that can be taken up by plants (Chapin III et al. 2012). Low soil water availability can result in water stress that reduces nitrogen uptake (Abreu et al. 1993).

Climate

Arguably, climatic conditions strongly influence crop growth as they determine water availability and energy for plant growth. To represent climatic conditions, we used time series of growing degree days (*gdd*) and annual precipitation sums (*prcp_sum_year*).

Macro socio-economy

Population density (*popdens*) in Europe, which is strongly related to the Gross Domestic Product (Pan et al. 2013), represents the broader socio-economic setting a farm is located in. Higher population densities are often found in low-intensity regions as the share of utilised area is lower compared to high-intensity regions (Refsgaard et al. 2011). The country (*country*) dummy was used to proxy country-specific characteristics (e.g., lifestyle, policies, management legacies, etc.) that either cannot be directly measured or only at low spatial or temporal resolution. The time dummy (*time*) captures all time-related variability that could not be explained by the set of explanatory variables.

Chapter V:
Archetypical patterns and trajectories of land systems in Europe

Regional Environmental Change (accepted)

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Abstract

Assessments of land-system change have dominantly focused on conversions among broad land-use categories, whereas intensity changes within these categories have received less attention. Considering that both modes of land change typically result in diverse patterns and trajectories of land-system change, there is a need to develop approaches to reduce this complexity. Using Europe as a case study, we applied a clustering approach based on self-organising maps and 12 land-use indicators to map (i) land-system archetypes for the year 2006, defined as characteristic patterns of land-use extent and intensity, and (ii) archetypical change trajectories, defined as characteristic changes in these indicators between 1990 and 2006. Our analysis identified 15 land-system archetypes, with low-intensity archetypes dominating (ca. 55% coverage) followed by high-intensity archetypes (ca. 26%). In terms of change, we identified 17 archetypical change trajectories, clustered in four broad categories. Stable land systems were most widespread (ca. 40% of the EU27), followed by land systems characterised by land-use conversions (ca. 26%), de-intensification trends (ca. 18%), and intensification trends (ca. 15%). Intensively used and intensifying land systems were particularly widespread in Western Europe, whereas low-intensity and de-intensifying land systems dominated in Europe's east. Comparing our archetypes with environmental and socioeconomic factors revealed that good accessibility and favourable topographic, climatic, and soil conditions characterised intensively managed areas. Intensification was also most common in these areas, suggesting an ongoing polarisation of intensification in favourable areas and de-intensification and abandonment trends in more marginal areas. By providing spatially and thematically improved maps of land-use patterns and changes therein, our archetypes could serve as useful inputs for more detailed assessments of ecosystem service demand and supply, as well as explorations of land-system change trade-offs, especially with regards to land-use intensity. Further, they could serve useful for identifying regions within which similar policy tools could be valuable to develop regionalised, context-specific land-management policies to steer European land systems onto desired pathways.

1 Introduction

Humans have affected more than 75% of the earth's ice-free surface by either land management or land conversions (Luyssaert et al. 2014, Ellis et al. 2010) making land use a major force of global environmental change (Haberl et al. 2007). Land use can change due to given demands for land-based products in two general ways: (i) conversions among broad land-cover/use categories (e.g., deforestation, farmland abandonment, urban expansion), leading to changes in the extent of these classes, and (ii) changing management practices (e.g., changes in mechanisation, fertiliser application, or wood harvesting), resulting in intensity changes within these broad land-cover/use categories. Both types of changes are commonly interlinked, resulting in complex patterns and trajectories of land-system change. Understanding this complexity is important to design and implement context-specific, effective policy measures (Rounsevell et al. 2012, Foley et al. 2011), but also to assess the impacts of land-system changes on biodiversity and ecosystem services.

The characterisation and mapping of typical land-change patterns and trajectories that consider both changes in extent and intensity across sectors and at the level of the land system as a whole is a powerful tool for understanding the complexity of land-system changes. Such an approach allows for identifying "syndromes" or "archetypes" of land-system change, which describe unique land-change patterns or processes that occur repeatedly across space. Archetypes facilitate a more integrative understanding of land-system changes, and, when combined with driving factors of land change, provide deep insights into change trajectories, some of which may remain uncovered if area extent, intensity, and driving factors are studied in isolation from each other (Müller et al. 2014).

Despite calls for such an integrative analysis (Verburg et al. 2009) and the growing recognition of the importance of land-use intensity (Luyssaert et al. 2014, Erb et al. 2013a, Lambin et al. 2000), most studies to date focussed on individual land-change processes, often conversions only, thereby neglecting feedbacks between land-use sectors (e.g., Estel et al. 2015, Kuemmerle et al. 2015, Hansen et al. 2013, Hatna and Bakker 2011, Kaplan et al. 2009, Feranec et al. 2007). Furthermore, most studies focus on local scales but assessments of land-system changes from landscape to regional to continental scales are also important because these are the scales predominantly targeted by policy making in agriculture, forestry, and nature conservation sectors (e.g., in the European Union). The few existing studies that have taken a more holistic approach to mapping land systems on broad scales have been restricted to one point in time (Václavík et al. 2013, van Asselen and Verburg 2012, Ellis and Ramankutty 2008), thereby neglecting land change, or solely focussed on land-cover change, but did not include information on land-use intensity (Stellmes et al. 2013, Hill et al. 2008). What is needed are analyses that (i) jointly consider area and intensity changes, (ii) include multiple sectors (e.g., agriculture, forestry), and (iii) at spatial resolutions and extents relevant for policy-making. Unfortunately, such an assessment has so far not been carried out for any region in the world.

Europe is an interesting case to study land-system changes as its large environmental, political, and socio-economic heterogeneity resulted in a diversity of land systems and multifaceted land-change pathways (Vos and Meekes 1999, Jepsen et al. 2015, Fuchs et al. 2015). Europe has also experienced a period of marked land-use change recently, including both changes in the extent and intensity of agriculture and forestry (Jepsen et al. 2015, Rounsevell et al. 2012). For example, the breakdown of the Soviet Union and the subsequent eastward expansion of the EU triggered widespread land-use change (Munteanu et al. 2014, Kuemmerle 2008), both in agriculture (Griffiths et al. 2013b, Müller et al. 2009) and forestry (Griffiths et al. 2013a, Ellis et al. 2010, Kuemmerle et al. 2007). Furthermore, changes in policy instruments (e.g., the Common Agricultural Policy) markedly influenced Europe's land system (Donald et al. 2002). Unfortunately, the spatial patterns and trends of these land-system changes remain only partly understood.

Our goal was to identify and map *Land-System Archetypes* (LSA) as well as *Archetypical Change Trajectories* (ACT) of land systems on a 1 km^2 grid for the EU27 between 1990 and 2006. Throughout this study, we understand land systems as a combination of land cover and land-use intensity patterns where the elements are linked through systemic interactions (following van Asselen and Verburg 2012). Our definition of land systems assumes that the co-occurrence of recurring, distinguishable combinations of land cover and land-use intensity patterns reflects their systemic interactions, though this cannot be directly observed. Within this, we define land use as the socioeconomic activities with which humans utilise land cover (Lambin et al. 2006) by management practices that can be characterised by different degrees of intensity. For the purpose of this paper, we define our archetypes as a regularly appearing and distinguishable combination of land cover and land-use intensity patterns (i.e., LSAs) or changes (i.e., ACTs) that are linked through systemic interactions. We used self-organising maps (SOMs), an unsupervised clustering technique, to map LSAs and ACTs. SOMs reduce high-dimensional data by grouping observations based on their similarity in terms of features and locations and are hence highly suited for our approach. We used the resulting archetypes for assessing land-system change and to compare observed changes with a range of socio-economic and environmental factors (hereafter referred to as "explanatory factors") that are known to drive land-system change. Our study goes beyond existing EU-wide typologies that focused on characterising landscapes or environmental conditions (van Eupen et al. 2012, Brus et al. 2012, Hengeveld et al. 2012, Duncker et al. 2012, Hazeu et al. 2011, Mücher et al. 2010, Westhoek et al. 2006, Metzger et al. 2005a, Meeus 1995) by explicitly focussing on land-system change and by incorporating land-use intensity metrics. Specifically, we ask the following research questions:

1. Which are archetypical patterns and change trajectories in Europe's land system?
2. How do land-system patterns and changes relate to each other?
3. What characterises archetypical patterns and change trajectories in terms of key explanatory factors of land change?

2 Material and methods

We compiled a set of 12 indicators representing the extent of broad land-use categories and the management intensity within these categories pertaining to agriculture and forestry for the entire EU27 and the years 1990 and 2006 (section 2.1 and Table SI V-1). We used self-organising maps (Kohonen 2001) to derive LSAs for the year 2006, using indicators of land-use extent and intensity from that year, as well as ACTs between 1990 and 2006 (see section 2.3 for the calculation of indicator change values, Figure V-1). Subsequently, we reviewed, refined, and labelled the outcomes of the SOM clustering in an expert workshop for both, LSAs and ACTs. We overlaid the resulting archetypes with 14 explanatory factors of land change (section 2.2 and Table SI V-2). Whenever possible, we gathered data at a spatial resolution of 1 km^2; otherwise we relied on data at the NUTS-3 level (Nomenclature des unités territoriales statistiques; i.e., Nomenclature of Territorial Units for Statistics).

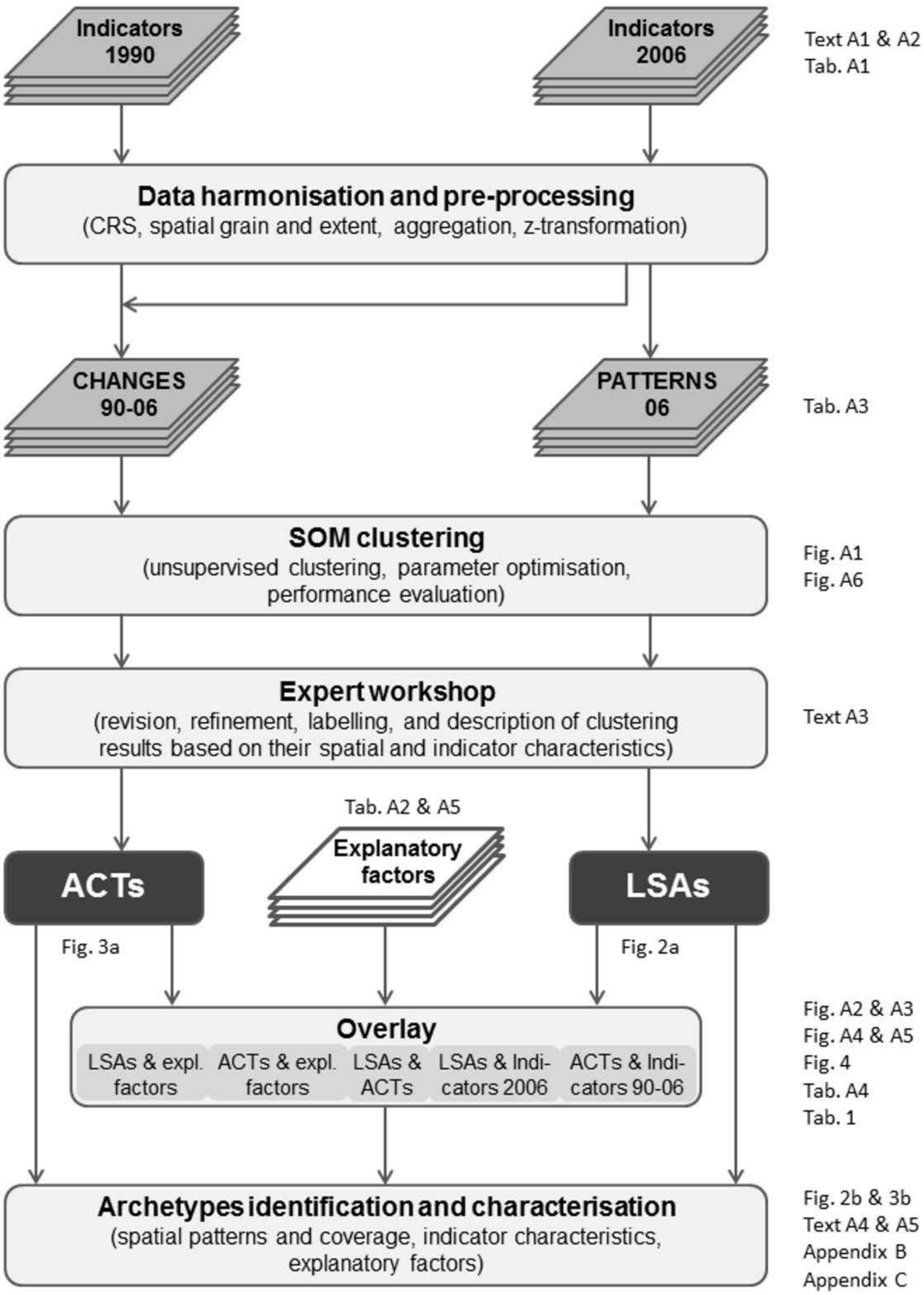


Figure V-1: Flowchart of the analysis steps with links to figures and tables in the SI. Note that the references to the Supplementary Information differ between the submitted manuscript and the version presented in this thesis. Materials from Appendix B can be found in Text SI V-6, Figure SI V-7, and Table SI V-6. Materials from Appendix C can be found in Text SI V-7, Figure SI V-8, and Table SI V-7.

2.1 Land-use indicators

Extent of broad land-use categories

We used a harmonised dataset on land use in Europe on a 1 km^2 grid for the time period between 1990 and 2006 (see Plutzar et al. 2015). Specifically, our dataset was generated using CORINE (Coordination of Information on the Environment) land-cover maps, sub-national forest data, and CAPRI (Common Agricultural Policy Regionalised Impact) data on biomass production in NUTS2 regions related to cropping, grazing, and forestry in an additive, closed-budget approach. From these datasets, we derived information on the extent of (i) built-up and infrastructure, (ii) cropland (arable, permanent, and fallow), (iii) forests and other wooded land, as well as (iv) grazing land (e.g., meadows, pastures) for both time steps. See Text SI V-1 in the Supplementary Information for details.

Fallow farmland and farmland abandonment is not covered well by CORINE. To characterise fallow farmland, we used a series of maps generated from Moderate Resolution Imaging Spectrometer (MODIS) satellite images for the years 2001-2012 at a spatial resolution of approximately 250 m (Estel et al. 2015), depicting the extent of fallow land annually. From these maps, we derived dominantly unmanaged farmland for the year 2006 by identifying pixels with at least four fallow years between 2001 and 2006 and at least ten fallow years between 2001 and 2012 following the definitions by Estel et al. (2015).

Intensity of broad land-use categories

Regarding land-use intensity, we used metrics for both, input and output intensity (Erb et al. 2013a, Kuemmerle et al. 2013). We used nitrogen application rates to assess the input intensity for croplands. Crop-specific nitrogen application rates for 1990 and 2006 were stratified into three classes: (i) low intensity with 0-50 kg N ha^{-1}, (ii) medium intensity with 50-150 kg N ha^{-1}, and (iii) high intensity with > 150 kg N ha^{-1} (Temme and Verburg 2011). To estimate input intensity on grasslands, we relied on stocking densities for cattle, sheep, and goats for the years 1990 and 2006 that were measured in livestock units (LSU) and classified into four classes: (i) 0-25 LSU km^{-2}, (ii) 25-50 LSU km^{-2}, (iii) 50-100 LSU km^{-2}, and (iv) >100 LSU km^{-2} (Neumann et al. 2009). We combined the two middle classes into a medium intensity class.

To assess the output intensity for croplands and grasslands for the years 1990 and 2006, we utilised data from a recent HANPP assessment for Europe (Plutzar et al. 2015). Specifically, we used the amount of biomass [tC km^{-2} yr^{-1}] harvested on arable cropland, permanent cropland, and grassland, and the spatial coverage [%] of the respective land-use categories to derive a harvesting intensity indicator [gC m^{-2} yr^{-1}]. To avoid inflated harvest intensity values due to high yields on very small areas, we used a maximum value of 1000 gC m^{-2} yr^{-1} (Haberl et al. 2007). To assess output intensity in forestry, we used spatially disaggregated data on sub-national wood production [m^{3} ha^{-1} yr^{-1}] (Verkerk et al. 2015). See Text SI V-2 in the Supplementary Information for details.

2.2 Explanatory factors of land-use change

For the selection of explanatory factors of land-use change, we built upon reviews and meta-analyses of land change (van Vliet et al. 2015a, Geist et al. 2006, Lambin and Geist 2006). We selected seven variables as location factors at a 1 km^2 resolution that were assumed to influence land-use change (Table SI V-2): accessibility, aridity index, environmental zones, growing degree days, population density, soil organic carbon, and terrain ruggedness. Furthermore, we selected seven potential underlying drivers that were for the most part only available on NUTS-3 level (Table SI V-2): economic activity, farm characteristics (capital input, economic size, labour input, land under agricultural use, subsidies), and protected area extent. We gathered data only for 2006, because most variables were not available for the entire study area for 1990 (e.g., because some countries were not in the EU then).

2.3 Methods

Data preparation

All data were harmonised to the same extent and projection (Lambert Azimuthal Equal Area projection). Our set of 12 land-use indicators consisted of binary and continuous variables. To avoid problems arising from using binary data for the calculation of changes as well as in the clustering, we aggregated all indicators to 3x3 km^2 cells by calculating the mean for continuous indicators and the relative area share of certain classes for binary indicators. Likewise, we aggregated the explanatory factors to the 3x3 km^2 grid by calculating the majority value for the environmental zones layer, the area share of protected areas, and mean values for the remaining factors. Data that were available for administrative units only (i.e., NUTS3-level with mean = 4,423 km^2 and s.d. = 5,882 km^2)

were rasterised to the same 3x3 km^2 resolution, assuming homogeneous distribution of values. To quantify changes in land-use extent and intensity, we calculated absolute differences for all 12 indicators between 1990 and 2006. Subsequently, we z-transformed the resulting differences to zero mean and unit standard deviation to make indicators comparable.

Self-organising maps

We used self-organising maps (SOMs), an automated clustering technique based on an unsupervised, competitive learning algorithm (Kohonen 2001). SOMs can be used to visualise high-dimensional data and reduce their complexity to fewer (often two) dimensions by grouping observations based on their similarity. In comparison to traditional cluster techniques such as k-means or hierarchical clustering, SOMs depend less on expert rules or supervised threshold selection and are not restricted by the number of input features (Václavík et al. 2013). Furthermore, SOMs preserve the typology of the input data by weighing more similar observations stronger in the clustering process (Ripley 1996). SOM-based algorithms have been widely applied in different fields, including geographic information science (Agarwal and Skupin 2008, Kohonen 2001) and land-system science (Václavík et al. 2013).

The parameterisation of SOMs requires, similar to k-means clustering, an *a-priori* definition of the desired number of clusters, which are typically organised in an output grid. Choosing an insufficient number of clusters in respect to the variability of the input data will result in clusters that are not well separated and inhomogeneous, while choosing too many clusters will result in splitting up homogeneous clusters. Hence, identifying the desired number of clusters is a key step to generate a meaningful cluster map.

To identify the ideal SOM parameterisation, we performed a sensitivity analysis with varying cluster dimensionalities ranging from 2x2 to 6x5. We determined both parameters by finding the natural breakpoint in the mean distance of the samples to their cluster centroid (Maulik and Bandyopadhyay 2002) and by evaluating the Davies-Bouldin cluster validity index that relates intra- and inter-cluster variability (Davies and Bouldin 1979). For LSAs, these indices suggested an optimum of 16 clusters and a 4x4 dimensionality (Figure SI V-1a). For ACTs, we selected 20 clusters and a 5x4 dimensionality (Figure SI V-1b). We used the *kohonen* (Wehrens and Buydens 2007) and *clusterSim* (Walesiak and Dudek 2014) packages in R (R Core Team 2014) to perform all analyses.

Post-processing of clustering results

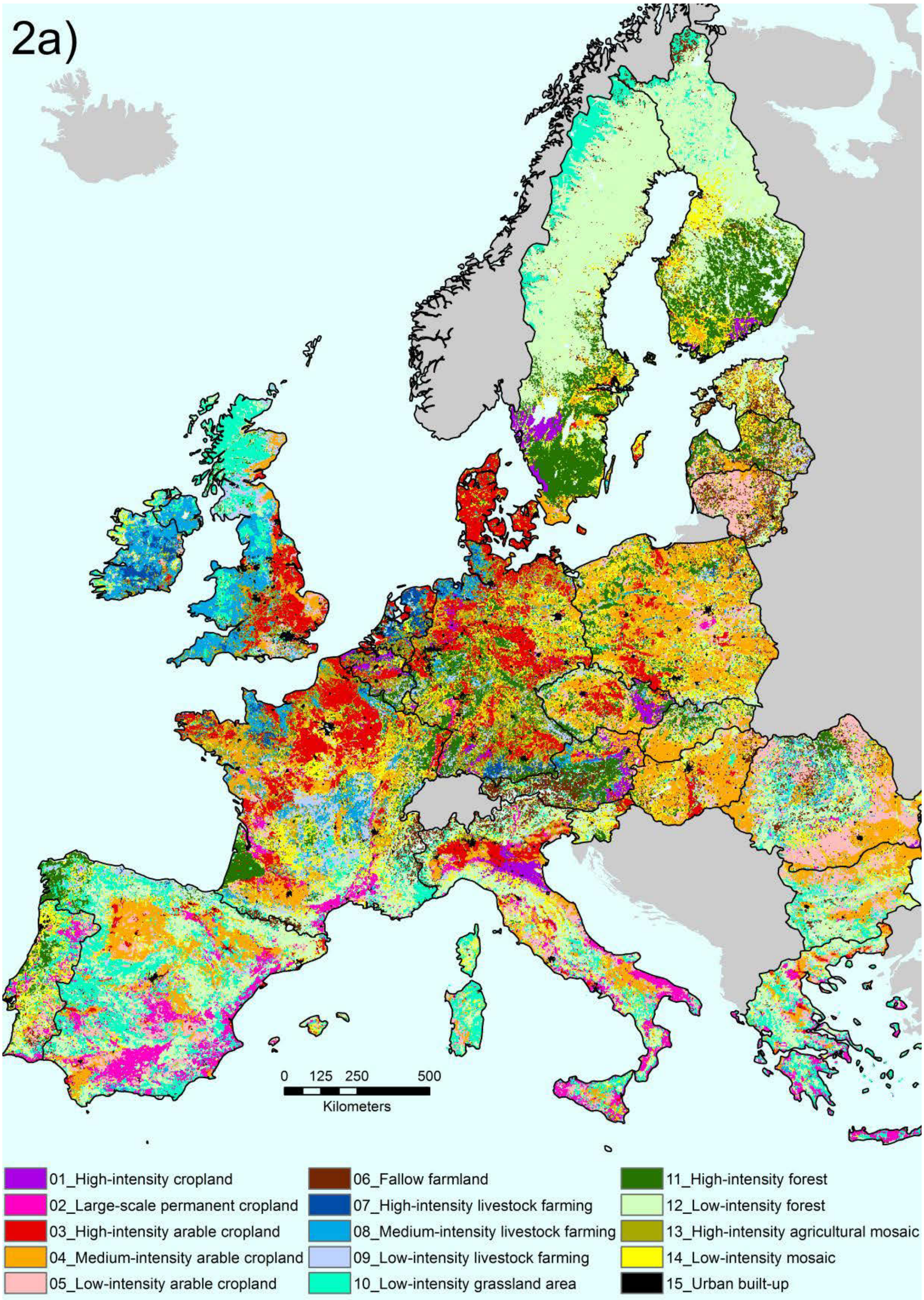
Once the clustering was completed, we mapped cluster memberships for all grid cells. We also created bar plots to assess the magnitude and direction of impact of each indicator used in the clustering for each cluster. Bar plots visualise indicators' z-scores averaged across all cells belonging to a specific cluster. Positive z-scores here refer to above-average, negative z-scores to below-average values regarding the indicator's overall mean for the entire study area (Table SI V-3).

In an expert workshop (Text SI V-3), we then used the clustering output to identify LSAs and ACTs and to describe and label each archetype based on its characteristics and spatial patterns. This led to the merging of four cluster pairs which were qualitatively similar. This resulted in a final set of 15 LSAs and 17 ACTs, which we overlaid to assess their spatial association and thus to assess which land change processes (ACTs) characterised and led to a given land-system archetype (LSA) during 1990-2006. We furthermore characterised LSAs and ACTs by investigating their co-occurrence with explanatory factors of land change by creating boxplots for each factor (cf. Table SI V-2) for each LSA and ACT separately (Figure SI V-2 and Figure SI V-3).

3 Results

3.1 Spatial patterns of Land-System Archetypes & Archetypical Change Trajectories

We mapped 15 Land-System Archetypes (Figure V-2a), which can be grouped into four broad land-use categories: (i) agriculture, pertaining to croplands and grasslands, (ii) forestry, (iii) mosaic landscapes, and (iv) urban areas. Within each category, LSAs were ordered along gradients of intensity, e.g. archetypes of high- or low-intensive arable croplands represent regions that were characterised by either high or low fertiliser application rates. Most LSAs were dominated by one land use, i.e. archetypes were characterised by indicators that pertained to one land use and exhibited above-average values whereas the remaining indicators were below or close to the study area average (Table V-1a). Figure V-2b provides a brief description of all LSAs and their spatial coverage. A detailed description of each LSA regarding its characteristics and spatial patterns is provided in Text SI V-6, Figure SI V-7, and Table SI V-6.


2a)
0 125 250 500
Kilometers
01_High-intensity cropland
02_Large-scale permanent cropland
03_High-intensity arable cropland
04_Medium-intensity arable cropland
05_Low-intensity arable cropland
06_Fallow farmland
07_High-intensity livestock farming
08_Medium-intensity livestock farming
09_Low-intensity livestock farming
10_Low-intensity grassland area
11_High-intensity forest
12_Low-intensity forest
13_High-intensity agricultural mosaic
14_Low-intensity mosaic
15_Urban built-up

2b)	Cluster	Description	Area [km^2]	Area share [%]
	LSA01	**High-intensity cropland:** high arable cropland cover and yields, accompanied by very high permanent cropland yields	55.269	1,31
	LSA02	**Large-scale permanent cropland:** high permanent cropland cover and above average permanent crop yields	158.526	3,75
	LSA03	**High-intensity arable cropland:** high fertiliser input, high arable cropland cover, and high arable yields	317.691	7,51
	LSA04	**Medium-intensity arable cropland:** medium fertiliser input, high arable cropland cover, and slightly above average arable yields	501.804	11,86
	LSA05	**Low-intensity arable cropland:** low fertiliser input and high arable cropland cover with average arable yields	259.497	6,13
	LSA06	**Fallow farmland:** high fallow farmland and low values for other indicators of agricultural intensity	166.410	3,93
	LSA07	**High-intensity livestock farming:** high livestock density, very high grassland cover, and very high grassland yields	39.303	0,93
	LSA08	**Medium-intensity livestock farming:** medium livestock density, very high grassland cover, and high grassland yields	169.029	4
	LSA09	**Low-intensity livestock farming:** low livestock density, high grassland cover, and slightly above average grassland yields	248.823	5,88
	LSA10	**Low-intensity grassland area:** very high grassland cover (often used for grazing) and low values for all other indicators	389.727	9,21
	LSA11	**High-intensity forest:** high forest cover and high wood production rates	351.918	8,32
	LSA12	**Low-intensity forest:** high forest cover and low values for all other indicators	817.992	19,33
	LSA13	**High-intensity agricultural mosaic:** high cropland and grass-land yields, high fertiliser input, and high livestock density with moderately high agricultural coverage and low forest cover.	191.565	4,53
	LSA14	**Low-intensity mosaic:** no marked differences from indicator mean values. Cropland and grassland cover as well as fertiliser and livestock density are slightly below average, while forest cover and arable yields are slightly above average	487.116	11,51
	LSA15	**Urban built-up:** high urban built-up cover and low values for all other indicators	76.194	1,8
			4.230.864	100

Figure V-2: Spatial patterns of Land System Archetypes for the EU27 (a) and respective cluster descriptions and statistics (b). Numbers in front of each archetype refer to its cluster number (cf. panel b). The colour code in the first column refers to the colour scheme used in panel a. Please refer to the data sheets of single LSAs (Figure SI V-7) for a detailed archetype description and a colour-blind safe visualisation of their spatial patterns.

Table V-1: Indicator-specific magnitude of impact for each Land System Archetype (a) and Archetypical Change Trajectory (b). The larger the deviance from the study area average, the higher the impact of a given indictor in characterising the respective LSA/ACT. The + and – (LSAs) as well as ↑ and ↓ (ACTs) signs indicate whether an indicator is above or below the study area average; the absence of any sign indicates no substantial deviance from the study area average. We used different thresholds for LSAs (+ from ≥ 0.5 up to 1 s.d., ++ from ≥ 1 up to 2 s.d., and +++ ≥ 2 s.d.) and ACTs (↑ from ≥ 0.25 up to 0.5 s.d., ↑↑ from ≥0.5 up to 1 s.d., and ↑↑↑ ≥ 1 s.d.) due to a smaller data range for ACTs. The same thresholds were applied to negative deviances. Hence, no substantial deviances were defined for s.d. between -0.5 and 0.5 (LSAs) and -0.25 and 0.25 (ACTs). HANPP (Human Appropriation of Net Primary Production) indicators represent the following input data: yields from harvest for arable cropland (HANPP harv arable), permanent cropland (HANPP harv perm), and grassland (HANPP harv grass).

a)	**Land-System Archetype**														
Indicator name	***01***	***02***	***03***	***04***	***05***	***06***	***07***	***08***	***09***	***10***	***11***	***12***	***13***	***14***	***15***
Cropland arable	+		++	++	++					-	-	-			
Cropland permanent		+++													
Fallow farmland						+++									
Grassland			-				++	++	+	++	-	-			-
Forest		-	-	-	-		-	-			++	++	-		-
Built up															+++
Low livestock density									+++						
Medium live-stock density								+++					+		
High live-stock density							+++								
Low nitrogen input					+++										
Medium nitrogen input	+			+++											
High nitrogen input			+++										+		
HANPP harv arable	+		+			-	+			-		-	++		
HANPP harv perm	+++												+		
HANPP harv grass							+++	+++	+			-	++		
Forest harvesting		-		-	-					-	+++				-

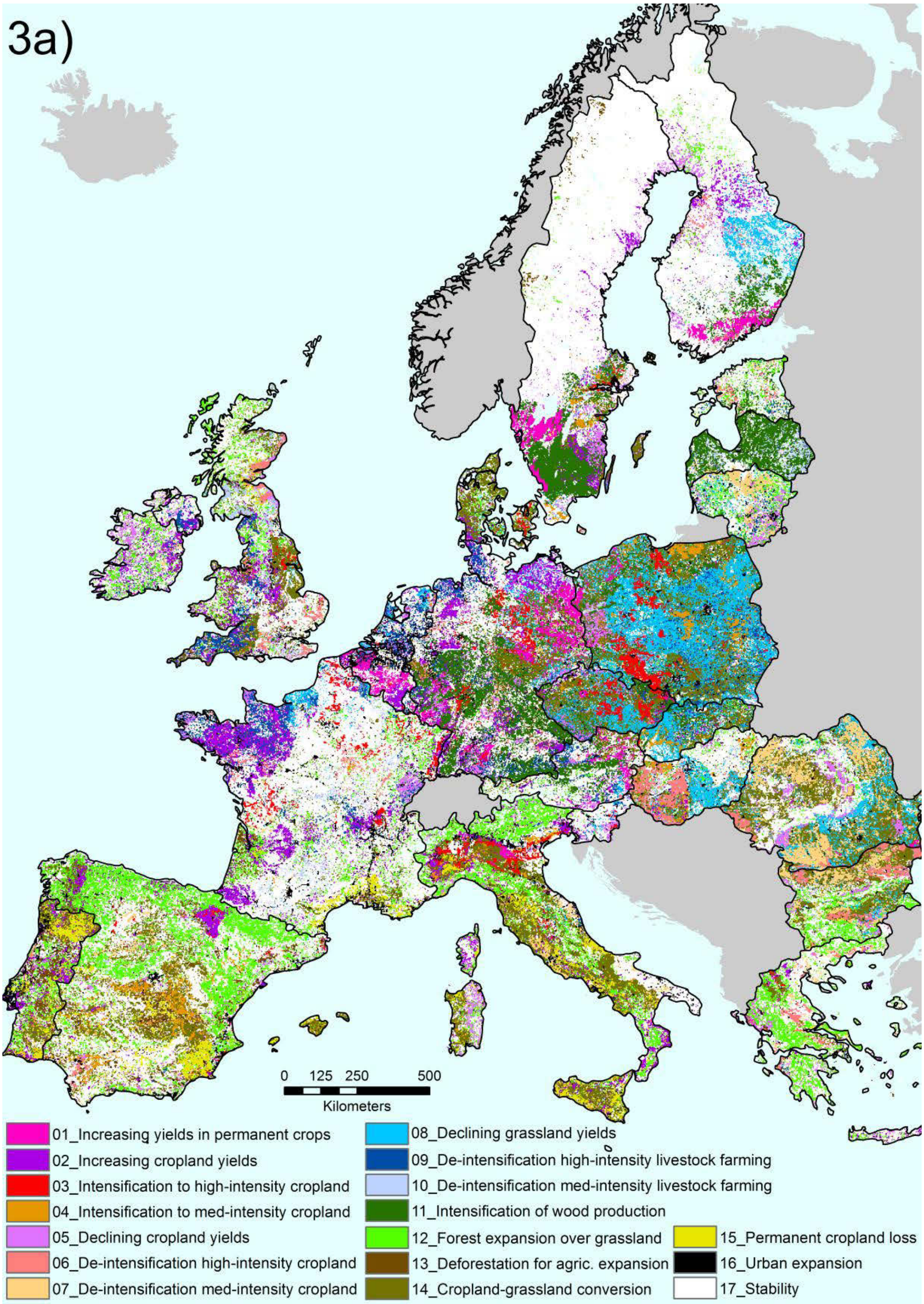
b) **Archetypical Change Trajectory**

Indicator name	***01***	***02***	***03***	***04***	***05***	***06***	***07***	***08***	***09***	***10***	***11***	***12***	***13***	***14***	***15***	***16***	***17***
Δ Cropland arable		↑	↓↓	↓↓		↓↓	↓↓	↓↓			↑	↑	↑↑	↓↓↓	↓		↑
Δ Cropland permanent													↑↑↑		↓↓↓	↓	
Δ Grassland			↑	↑↑		↑	↑↑	↑↑			↓	↓↓↓	↑↑	↑↑↑	↑↑↑	↓	
Δ Forest			↓									↑↑↑	↓↓↓		↑↑	↓	
Δ Built up															↑	↑↑↑	
Δ Low livestock density										↑↑↑							
Δ Medium livestock density									↑↑↑	↓↓↓							
Δ High livestock density									↓↓↓								
Δ Low nitro-gen input			↓	↓↓↓		↑	↑↑↑										
Δ Medium nitrogen input			↓↓↓	↑↑↑		↑↑↑	↓↓↓										
Δ High nitro-gen input			↑↑↑			↓↓↓											
Δ HANPP harv arable		↑↑↑			↓↓↓			↓							↑↑		
Δ HANPP harv perm	↑↑↑				↓	↓											↓
Δ HANPP harv grass	↑							↓↓↓					↑↑		↑		
Δ Forest harvesting	↑			↓		↓	↓				↑↑↑		↓↓↓		↓	↓	

Regarding the spatial coverage of LSAs, low-intensity archetypes dominated much of the EU, accounting for more than 55% of its terrestrial surface. High-intensity archetypes had a substantially smaller extent (26%) of which intensive agriculture was mainly located in central Europe, the UK, and Ireland, sometimes co-occurring with intensive forestry. Medium- to low-intensity agriculture as well as low-intensity mosaic landscapes occurred predominantly in the eastern parts of Europe, highlighting a marked east-west divide in Europe's land-use patterns. A mixture of intensively managed permanent crops, low-intensity grazing and mosaics characterised the Iberian Peninsula, locally complemented with medium-intensity croplands. Scandinavia was characterised by high-intensity forestry systems in the southern parts and low-intensity forestry in the remainder, complemented with low-intensity grasslands in the northern, mountainous regions. Fallow farmland showed distinct spatial patterns, occurring mainly in mountainous regions (Pyrenees, Alps, and Carpathians) as well as in the Baltic countries and eastern Poland (c.f. Text SI V-4 for details).

We identified 17 Archetypical Change Trajectories (Figure V-3a), which can be grouped into four general types of trends: (i) Intensification and (ii) de-intensification within a certain land-use category, (iii) land-use conversions, and (iv) stability. As an example, the archetype intensification of wood production represented regions predominantly characterised by increases in wood harvesting. Most ACTs were dominated by changes in only a few (often one) land-change indicators (Table V-1b). Land-use conversions mostly represented de-intensification trends, except for urban expansion and forest loss for agricultural expansion. Figure V-3b provides a brief description of all ACTs and their spatial coverage. A detailed description of each ACT regarding its characteristics and spatial patterns is given in Text SI V-7, Figure SI V-8, and Table SI V-7.

Stability was the dominant ACT, covering more than 40% of the EU's surface. De-intensification processes (e.g., cropland-grassland conversion or yield decreases on grasslands) were the spatially most widespread changes we found (approximately 30% coverage). Intensification trajectories (e.g., increases in yields or fertiliser input) had a markedly lower extent (approximately 11%) and were not observed on grasslands. It is noteworthy that even regions that were classified into one of the change archetypes were often characterised by relative stability as only a few indicators (often only one or two) changed, while many others remained stable between 1990 and 2006. Stable land systems were particularly widespread in Central, Western, as well as Northern Europe. The central part of the EU had marked trends of intensifying wood production and increasing cropland yields but also cropland-grassland conversions and urban expansion. The eastern part of the EU was mainly characterised by de-intensification but smaller regions experienced cropland intensification. In the Mediterranean Region, large-scale de-intensification such as permanent cropland loss, cropland-grassland conversions, or forest expansion over grassland accompanied with substantial coastal urban expansion was typical (cf. Text SI V-5 for details).


3a)
0 125 250 500
Kilometers
01_Increasing yields in permanent crops
02_Increasing cropland yields
03_Intensification to high-intensity cropland
04_Intensification to med-intensity cropland
05_Declining cropland yields
06_De-intensification high-intensity cropland
07_De-intensification med-intensity cropland
08_Declining grassland yields
09_De-intensification high-intensity livestock farming
10_De-intensification med-intensity livestock farming
11_Intensification of wood production
12_Forest expansion over grassland
13_Deforestation for agric. expansion
14_Cropland-grassland conversion
15_Permanent cropland loss
16_Urban expansion
17_Stability

3b)	Cluster	Description	Area [km²]	Area share [%]
	ACT01	**Increasing yields in permanent crops:** above average increases in permanent cropland yields	72.801	1,72
	ACT02	**Increasing cropland yields:** above average increases in arable crop yields	200.790	4,75
	ACT03	**Intensification towards high-intensity cropland:** shift from medium towards high fertiliser input on arable cropland	72.090	1,7
	ACT04	**Intensification towards medium-intensity cropland:** shift from low towards medium fertiliser input on arable cropland	55.764	1,32
	ACT05	**Declining cropland yields:** above average decreases in arable cropland yields	146.205	3,46
	ACT06	**De-intensification of high-intensity cropland:** shift from high towards medium fertiliser input on arable cropland	71.784	1,7
	ACT07	**De-intensification of medium-intensity cropland:** shift from medium towards low fertiliser input on arable cropland	98.649	2,33
	ACT08	**Declining grassland yields:** above average decreases in grassland yields	251.640	5,95
	ACT09	**De-intensification of high-intensity livestock farming:** shift from high-intensity towards medium-intensity livestock density	99.396	2,35
	ACT10	**De-intensification of medium-intensity livestock farming:** shift from medium towards low livestock density	73.089	1,73
	ACT11	**Intensification of wood production:** above average increases in wood production rates	241.380	5,71
	ACT12	**Forest expansion over grassland:** above average increases in forest cover at the expense of grassland cover	371.853	8,79
	ACT13	**Deforestation for agricultural expansion:** above average decreases in forest cover and harvesting and increases in arable and permanent cropland cover	56.970	1,35
	ACT14	**Cropland-grassland conversions:** above average decreases in arable cropland and increases in grassland cover	476.118	11,25
	ACT15	**Permanent cropland loss:** above average decreases in cropland cover dominated by permanent crops and increases in grassland and forest cover	75.609	1,79
	ACT16	**Urban expansion:** above average increases in urban built-up cover	129.600	3,06
	ACT17	**Stability:** no substantial changes for any indicators	1.737.126	41,06
			4.230.864	100

Figure V-3: Spatial patterns of Archetypical Change Trajectories for the EU27 (a) and respective cluster descriptions and statistics (b). Numbers in front of each archetype refer to its cluster number (cf. panel b). The colour code in the first column refers to the colour scheme used in panel a. Please refer to the data sheets of single ACTs (Figure SI V-8) for a detailed archetype description and a colour-blind safe visualisation of their spatial patterns. Note that we used the term "cropland" representatively for arable croplands in the ACT labels for the sake of brevity.

3.2 Trajectories of land-system change

Spatial overlay between LSAs and ACTs

Cross-tabulating the spatial patterns of Land-System Archetypes and Archetypical Change Trajectories (Table SI V-5) revealed that the largest spatial overlap existed between stability (ACT17) and low-intensity forest (LSA12) with approximately 600,000 km^2. Stability had the largest spatial overlap with the majority of LSAs (11 out of 15), i.e. that these LSAs did not experience changes in comparison to the situation in 1990 (Figure V-4, upper panel). Only few LSAs were clearly influenced by only one dominant ACT, such as increasing yields in permanent crops (ACT01) on high-intensity cropland (LSA01), urban expansion (ACT16) on urban built-up (LSA15), and to a lesser degree intensification of wood production (ACT11) on high-intensity forest (LSA11). Interestingly, cropland-grassland conversion (ACT14) co-occurred with all three intensity levels of cropland management (LSA03-05).

We found seven ACTs that led to one dominant LSA in 2006 (Figure V-4, lower panel), e.g. the intensification to high-intensity cropland (ACT03) that was associated with high-intensity arable cropland (LSA03) in 2006, and four ACTs that were mostly related to one LSA. The remaining ACTs did not exhibit any clear trends into specific LSAs, and most LSAs were thus influenced by multiple ACTs or remained stable compared to 1990.

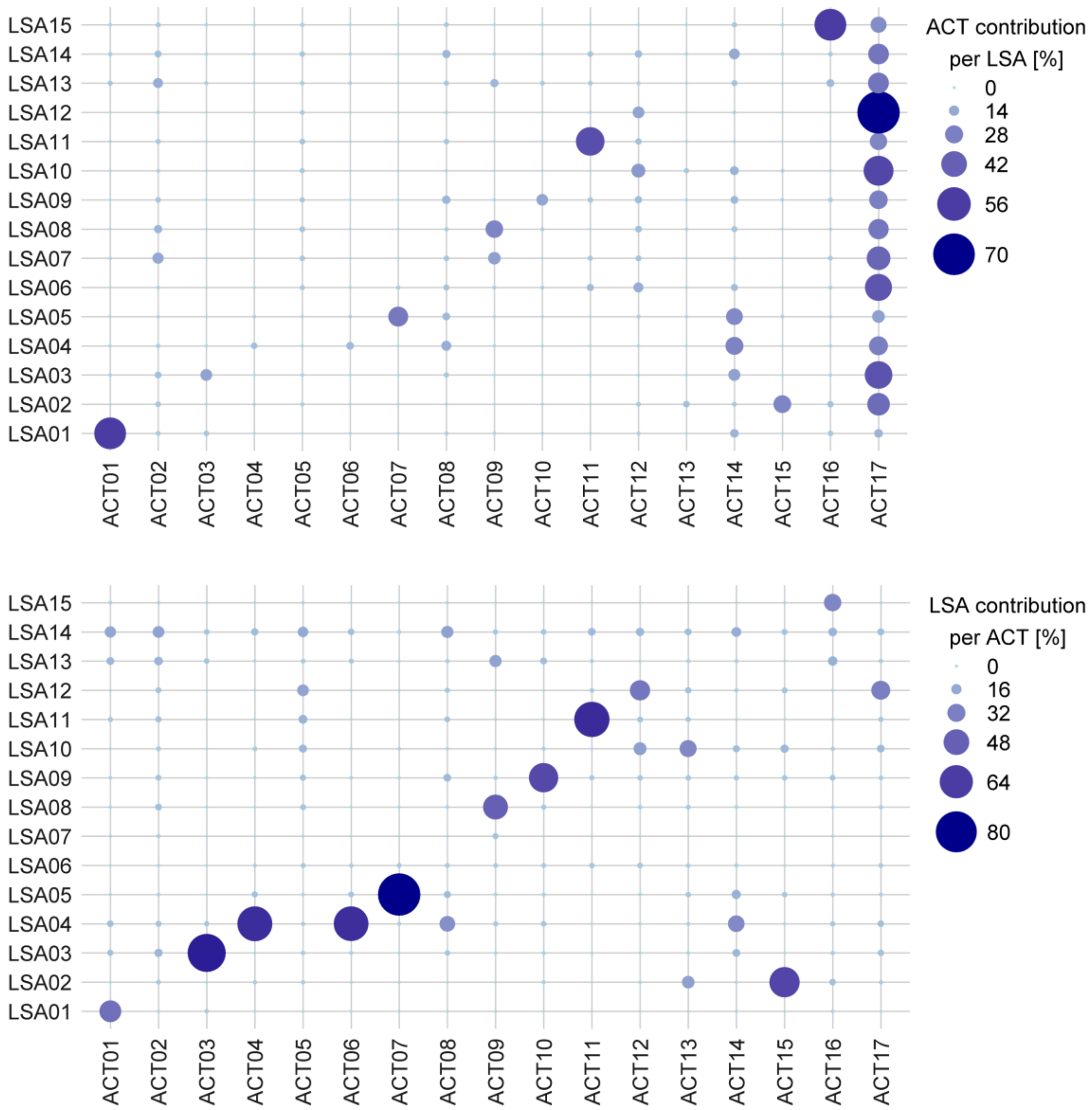


Figure V-4: Spatial coverage [%] of each ACT per LSA (upper panel) and of each LSA per ACT (lower panel). Rows (upper) and columns (lower) sum up to 100% spatial extent. Circle sizes and colour gradient depict the magnitude of co-occurrence.

Land-System Archetypes and explanatory factors

We compared spatial patterns in Land-System Archetypes with those of explanatory factors (Table SI V-4 and Figure SI V-2). Managed land systems pertaining to croplands (LSA01-05), grasslands (LSA07-09), and forests (LSA11) were generally characterised by good accessibility and low terrain ruggedness. For these areas, arid climatic conditions were observed on less-intensively managed croplands and especially for permanent crops. Aridity indices were above-average for managed grasslands and forests. Growing degree days (GDDs) for permanent crop areas and low-intensity cropland exceeded the study area average. On managed land systems, soil organic carbon was above-average only on managed grasslands. Socio-economic factors were generally high for all managed land systems, especially for croplands and forests. However, we observed decreasing trends of socio-economic values with less intensively managed areas (e.g., economic size, labour or capital input, and subsidies on croplands or economic size on grasslands). Contrasting with this, labour input exhibited an increasing trend with less-intensive grassland management. High-intensity mosaics (LSA13), which were characterised by multiple and mostly intensively managed land systems, were similar to intensively managed croplands (LSA03-05) in terms of socio-economic factors, accessibility, and terrain ruggedness.

Land systems that were not managed showed distinct differences to managed land systems. Fallow farmlands (LSA06) and semi-natural areas (LSA 10 and 12) revealed above average travel time, terrain ruggedness, aridity index, and soil organic carbon while growing degree days and most of the socio-economic factors were below the study area average. Two LSAs with distinct characteristics regarding their co-occurrence with explanatory factors were low-intensity mosaics (LSA14) that generally did not reveal marked deviations from the study area averages and urban built-up (LSA15) that exhibited the best accessibility, the lowest terrain ruggedness, and the highest economic activity among all LSAs. Most LSAs were mainly located in the Continental and Central Atlantic zone, except permanent crop cultivation areas (Mediterranean zones) and low-intensity forests (Boreal zone) (Figure SI V-4, top). Protected areas had the highest shares in low-intensity LSAs, especially on fallow farmland and low-intensity grassland areas. All agricultural areas revealed markedly lower shares of protected areas (Figure SI V-5, top). We found substantial variability across LSAs in terms of explanatory factors. Aridity index and growing degree days revealed the lowest variability across LSAs whereas economic activity and population density showed the highest variability.

Archetypical Change Trajectories and explanatory factors

Comparing Archetypical Change Trajectories with explanatory factors (Table SI V-4 and Figure SI V-3) showed that stability (ACT17) was generally observed where conditions were close to the study area average for all investigated explanatory factors. Intensifying land systems (ACT01-04 for croplands and ACT11 for forests) were generally characterised by good accessibility, low terrain ruggedness, and above-average socio-economic conditions, except for areas with low-level fertiliser intensification. Along with these general patterns, we also observed land-use specific conditions. ACTs related to fertiliser intensification (ACT03-04) were found in regions with below-average soil organic carbon contents, travel time to major cities, and aridity indices. For areas of intensifying wood production (ACT11), especially subsidies and labour input were above the study area average.

De-intensifying land systems exhibited a more nuanced picture regarding the co-occurrence of ACTs and explanatory factors. De-intensifying croplands (ACT05-07) and grasslands (ACT08-10) were found to be associated with good accessibility and below-average terrain ruggedness, likely due to their former function as high- or medium-intensive croplands, while aridity indices and growing degree days were close to the study area average. Soil organic carbon was above average for both livestock-related ACTs (ACT09-10). Socio-economic conditions were generally unfavourable (e.g., low economic activity, high labour input) on areas of declining grassland yields (ACT08). Areas of low-level de-intensification of livestock farming (ACT10) were associated with generally above-average socio-economic factors, differing from average conditions on de-intensifying croplands and high-intensity livestock areas.

Land systems that underwent land-use conversions were characterised by specific environmental and socio-economic conditions. Forests expanding over grasslands (ACT12) were associated with below-average socio-economic conditions as well as unfavourable accessibility and terrain ruggedness. Forest loss for agricultural expansion (ACT13) was found in regions characterised by below-average aridity indices, subsidies, and capital input as well as above average growing degree days. Conversions from cropland to grassland (ACT14) were associated with below-average terrain ruggedness and travel time while socio-economic factors were generally above or close to the study area average. Areas where permanent crops declined (ACT15) were characterised by all socio-economic factors, soil organic carbon contents, aridity indices, and travel time being below average. Most ACTs were mainly located in the Continental zone, except permanent cropland loss and deforestation for agricultural expansion (Mediterranean zones) and de-intensification of cropland (Pannonian zone) (Figure SI V-4, bottom). Protected areas had the highest shares in forest-related ACTs and were markedly low on croplands and in expanding urban areas. Areas of yield increases reveal relatively high shares of protected areas (Figure SI V-5, bottom).

4 Discussion

Disentangling the complexity of pattern, trajectories, and driving factors of land-use change is a major challenge in land-system science. In this regard, identifying high-level, archetypical patterns and trajectories in land systems is an important step for assessing the outcome of land change across larger regions and for a more context-specific, regionalised policy making. We mapped and characterised *Land-System Archetypes* (LSAs) and *Archetypical Change Trajectories* (ACTs) for Europe for the period between 1990 and 2006, using land-change indicators pertaining to both land-use extent and intensity, and overlaid these archetypes with a range of explanatory factors of land change.

4.1 Key insights: Land-System Archetypes

Regarding the spatial patterns of land systems (i.e., LSAs), three major insights emerged. *First, we identified a distinct east-west divide in terms of land-use intensity in Europe*. This east-west divide seems to at least partly reflect legacies from the strong divide in Europe in a Western and Eastern Bloc after World War II and until 1989. Despite the mutual aim of increasing agricultural production after World War II, institutional paradigms and socio-economic conditions differed markedly with a capitalistic, market-driven economy in Western Europe and a planning economy in Eastern Europe. Land reforms (expropriation and collectivisation) in Eastern Europe lead to generally larger, and often heavily industrialised, farms than in Europe's west (Niedertscheider et al. 2014, Lerman et al. 2004). At the same time, some landscapes characterised by marginal farming conditions where never industrialised to the extent that occurred in Western Europe (Sutcliffe et al. 2014, Fischer et al. 2012, Palang et al. 2006).

The collapse of the Socialist Bloc in the early 1990s triggered another period of diverging land use, as agricultural and forestry sectors in many Eastern European countries were restructured, and many state-own farming and forestry enterprises went bankrupt due to the loss of financial support (e.g., guaranteed prices), the disappearance of formerly guaranteed markets, and the emergence of outside competition (Kuemmerle et al. 2008, Müller et al. 2009, Müller et al. 2013, Donald et al. 2002). Together, this resulted in drastic declines of harvested areas, crop yields, and livestock numbers in many former Socialist countries (Rozelle and Swinnen 2004). These de-intensification trends in Eastern Europe occurred at a time when much of the support for agriculture in Europe's west was still production-oriented, boosting agricultural production in many areas with favourable socio-economic conditions. However, the Common Agricultural Policy (CAP) subsidy payments in the EU were adjusted in 1992 (MacSharry reforms) and income support was to some extent de-coupled from production. De-intensification trends in the EU's east were partly reversed with the EU accession of former Socialist countries, enabling farmers to access CAP payments (Sutcliffe et al. 2014). Yet, the full effects of the CAP are likely not reflected in our dataset (as countries joined the EU in 2004 and 2007 only).

Second, long-term land-use legacies from before World War II are still apparent in the spatial patterns of land systems. Effects of past land use on the state of current land systems can persist for decades or centuries (Thompson et al. 2013, Foster et al. 2003) and create path dependencies in land-system change (Brown et al. 2005). For example, the former eastern border of the German Empire, which underwent a first wave of agricultural intensification already in the late 19th century and was characterised by large farming estates (Niedertscheider et al. 2014) contrasting with neighbouring areas in Poland dominated by family- and small-scale farming, is still observable today. These Polish areas are currently characterised by high-intensity management systems in forestry and especially crop production. Likewise, the central European countries generally experienced an earlier start of agricultural industrialisation compared to Europe's east and south (Jepsen et al. 2015), with new crops and rotation patterns, and benefited from the European Recovery Program (ERP, a.k.a. the Marshall Plan) that boosted intensification after World War II, and these areas continue to be Europe's most intensively used areas.

Third, agro-climatic conditions remain a strong determinant of land-system patterns in Europe. Despite technological innovation and substantial investments into overcoming agro-climatic conditions (e.g., drainage, fertilisation, irrigation), agro-climatic conditions remain an important determinant of land-use intensity. Forest and grassland landscapes dominated in those areas with disadvantageous edaphic and climatic conditions for intensified agriculture, such as in Northern (too cold and wet) and Southern (too warm and dry) Europe (Metzger et al. 2005a, Mücher et al. 2010). In contrast, high-intensity systems prevailed mainly in Central and Western EU, regions that exhibit favourable agro-climatic conditions. Interestingly though, both intensified systems in unfavourable agro-climatic zones, as well as pockets of low- to medium-intensity systems in favourable regions (e.g., Eastern Europe) occurred, highlighting the importance of institutional and socio-economic conditions.

4.2 Key insights: Archetypical Change Trajectories

Regarding land-system change (ACTs), four major insights emerged. *First, increasing or stable yields on shrinking cropland extent were common*. Such polarisation trends (i.e., the co-occurrence of cropland intensification and abandonment), often go along with rural population declines (Weissteiner et al. 2011) and (peri-)urbanisation (Plieninger et al. 2014) and have been reported at national (FAOSTAT 2015) and local scales (Stellmes et al. 2013, Piquer-Rodríguez et al. 2012), and our study provides further evidence for these trends. Reasons for this polarisation are likely diverse (Plieninger et al. 2014), but lead to a specialisation, intensification, and concentration of crop production in regions that remain competitive, often with the help of trade regulations or subsidies, whereas marginal areas are set-aside (e.g., to receive respective CAP payments) or abandoned as land-use becomes unprofitable (Fischer et al. 2012, Antrop 2005).

Second, forestry intensification and forest area expansion both occurred in Europe, yet often not in the same regions. The observed forestry intensification in Germany, Sweden, Finland, and the Baltics corresponds well with the location of traditional wood production regions (Levers et al. 2014, Verkerk et al. 2015). Forest area increased generally throughout Europe during our study period, especially in Europe's east and the Mediterranean (e.g., Spain), due to afforestation and forest encroachment on abandoned agricultural land (Forest Europe et al. 2011). As forest cover increase thus often occurs in marginal agro-climatic areas (Stellmes et al. 2013, Hill et al. 2008), these areas are not the prime regions for wood production either.

Third, strong urbanisation trends in some European areas, mainly along the coasts and in Western Europe, often go along with abandonment and declining land-use intensity in the hinterlands. This picture can be partly likely linked to rural-urban migration caused by increasing per capita GDP in urban areas (Seto et al. 2011) and diminishing income opportunities in marginal areas (Ramankutty et al. 2002). These trends were observed, for example, in Italy (Niedertscheider and Erb 2014), the Mediterranean (Stellmes et al. 2013, Hatna and Bakker 2011, Weissteiner et al. 2011), Switzerland (Gellrich et al. 2007), and Eastern Europe (Müller et al. 2009, Kuemmerle et al. 2008). Abandonment in Europe therefore generally appears to refer to two functionally different types: (i) rural exodus type of abandonment, where diminishing income opportunities in rural areas and urbanisation led to abandonment (e.g., mountainous areas, the Mediterranean), and (ii) the post-socialist type of abandonment, triggered by the drastic institutional and socio-economic reorganisation after 1990, with both trends co-occurring in Eastern Europe.

Fourth, stable land-use patterns were a main characteristic of many landscapes in the EU between 1990 and 2006. In our analysis, stability refers to no or minor changes in land systems, independent of the observed level of management intensity (i.e., whether low/medium/high-intensive management practices were applied). The observed widespread stability is surprising, given the increasing consumption of agricultural and forestry products in Europe over our observation period (Kastner et al. 2015). Three phenomena likely explain this stability. First, stability may be expected in regions where intensification (and polarisation) trends have already advanced for long time periods. This is particularly the case for Western and Central Europe, where fertile regions are characterised by long land-use histories, an early industrialisation of land use (Jepsen et al. 2015), low yield gaps (Neumann et al. 2010, Licker et al. 2010), and a quick adoption of the latest technologies. Land-use in more marginal areas has contracted already for many decades, with forest transitions in these areas in the 19th and early 20th centuries (Kuemmerle et al. 2015, Meyfroidt and Lambin 2011).

A second major explanation for the widespread stability observed in the western EU are land-use policies that hinder many drastic changes in land-systems across the EU. Most importantly, many EU-subsidies target at maintaining the current configuration of Europe's land system, for example by providing farmers in less favoured areas with production support with the goal of maintaining land use in such, often more traditional, landscapes (Fischer et al. 2012). Also, the decoupling of CAP payments in 2003 resulted in relatively stable land-use patterns. For example, the preservation of extensive grazing systems through direct payments avoided land abandonment and hence supported the status quo with the conservation of these rural landscapes (Lefebvre et al. 2012). The importance of these CAP-related subsidies is emphasised by the finding of a recent study that production would decline by up to 12% should these subsidies be removed (Anderson et al. 2006).

Third, the displacement of land-based production to regions outside the EU appears to be a major driver of the observed stability of Europe's land systems. The "outsourcing" of land-based production to other world regions, where production is less costly, now accounts for roughly one third of the land needed for satisfying European demands, and this number has been increasing rapidly in our observation period (Kastner et al. 2014). This likely reduced the pressure to intensify and utilise more marginal farm- and forestland in Europe considerably, albeit at the cost of exporting environmental trade-offs and a growing dependence on biomass imports (Kastner et al. 2014).

4.3 Robustness and limitations

When interpreting our LSA and ACT patterns we caution that our analyses emphasise broad-scale patterns and trends that may not always hold at local scales. For example, LSAs and ACTs were defined and labelled regarding the most dominant land-use patterns and processes, although other land change processes may occur locally or at a spatial grain below that of our analysis. Second, our ACTs are defined based on the dominating land-change process, but the extent of change may be small. For example, a region characterised by forest expansion over grassland may experience a small reduction of grassland cover due to abandonment and forest expansion, yet may still remain grassland-dominated. The comparison of ACTs and LSAs resolves such ambiguities, highlighting the need for interpreting both jointly.

Third, additional data, for example maps on changes in mechanisation, irrigation, or rotation lengths, would have helped to further refine our assessment but are currently not available, neither as vector nor as raster data. The increasing availability of spatially and temporally high-resolution satellite images provides tremendous opportunities for improving the current generation of land-use indicators, including indicators on management intensity (Kuemmerle et al. 2013). For example, remote sensing images have been used map agricultural abandonment across Europe (Estel et al. 2015) and this information was utilised in our analysis. Fourth, spatial mismatches between LSAs/ACTs raster data (raster data at 3x3 km^2 resolutions) and socio-economic drivers (vector data at NUTS3 level, cf. Table SI V-2) might have led to uncertainty in cluster characterisations since driver values were assumed constant across administrative units. Although all our indicators were raster layers at 1 km^2 resolutions (except for data on agricultural abandonment, which was of higher resolution, cf. Table SI V-1), scale-related uncertainties cannot be ruled out since these indicators were originally derived based on data at different spatial scales (e.g., LUCAS data [point observations], CORINE land-cover [100 m^2 raster data], or CAPRI data [polygons]).

Fifth, our results depend to some extent on the SOM parameterisation and a different number of clusters would lead to different results in terms of indicator importance for each cluster. To address this issue, we used statistical measures to determine the optimal cluster number and then evaluated and merged clusters during an expert workshop, which served as a plausibility check for our results. We also compared LSA and ACT maps based on the different SOM parameterisations that generally revealed high similarity (results not shown). Moreover, we calculated the distance of each raster cell to the cluster centre, suggesting most regions were well captured with our LSAs and ACTs (Figure SI V-6).

Finally, our analyses relied on an array of input layers on the extent and intensity of land use, and our analyses thus rest on the quality of these input layers. For example, CORINE land-cover class accuracies are arguably a source of uncertainty within our approach, especially for heterogeneous classes such as transitional woodlands or complex cultivation patterns. To address this misclassification problem, we reconciled NUTS2 census statistics with our indicator layers, both for the extent of land-use types and for biomass flows (i.e., land-use intensity), to minimise the error at the aggregate level. Generation, input data, and uncertainty of these datasets are discussed at length elsewhere (Plutzar et al. 2015, Estel et al. 2015, Temme and Verburg 2011, Neumann et al. 2009, Verkerk et al. 2015). These data represent, to the best of our knowledge, the most spatially detailed and thematically comprehensive set of land-change indicators compiled, and our analyses generally lead to highly plausible results. Yet some patterns in our dataset, for example large changes in permanent crop yields in Sweden, Finland, and eastern Germany, may represent data artefacts, which – in turn – might affect the accuracy of our results. Misclassifications in land cover or uncertainty in land-use intensity indicator values could have resulted in specific indicator characteristics that were picked up by the clustering algorithm and ultimately led to uncertainty in the clustering. Still, we feel that outliers are unlikely to affect the overall patterns and clusters we detected.

5 Conclusions

We here used self-organising maps to map and characterise archetypical land-system change trajectories across the EU for the period 1990 to 2006 using information on patterns of and changes in the extent and intensity of broad land-use classes, with a focus on agriculture and forestry. We found a distinct east-west divide in terms of land-use intensity, with high-intensity systems in Western and Central Europe and lower-intensity systems in the Eastern EU, mainly reflecting land-use legacies from before World War II and from the strong divide in Europe in a Western and Eastern Bloc until 1989. Furthermore, agro-climatic conditions remain a strong determinant of land-system patterns in Europe, with high-intensity systems generally exhibiting favourable agro-climatic conditions. Most European land systems were characterised by stability over the study period, but we also observed considerable areas with a land-use polarisation trend (i.e., increasing yields on shrinking cropland area). Forestry intensification did often not occur where forests expanded, likely due to differences in the productivity of these regions. Finally, strong urbanisation trends occurred mainly along coasts and in urban agglomerations in Western Europe, often in concert with decreasing land-use intensity in the hinterlands.

Our approach highlights that the combination of a clustering algorithms and an expert-based assessment can help to substantially reduce complexity in land-system change, even across an environmentally and socio-economically diverse region such as Europe. This is promising, given calls for more context-specific, regionalised policy making (e.g., the CAP transfer to Eastern European countries; Gorton et al. 2009), as our archetypes could be a first-order approximation of units within which similar policy tools could be useful. Likewise, our archetypes could be useful templates in which to explore ecosystem service demand and supply, land-use effects on biodiversity, and trade-offs between production and non-provisioning services since they provide spatially and thematically improved maps of land-use patterns and changes therein. For example, species range maps that are usually generated based on land-cover data could be improved by our holistic land-systems approach, explicitly including the land-use intensity dimension. Also, knowledge on which driving factors are associated with specific patterns and trajectories of land systems can inform policy makers and provide indications for implementing actions.

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Supplementary Information

Table SI V-1: Indicators of land-use extent and land-use intensity.

	Indicator	Short description	Unit	Time period	Reso-lution	Source
Land-use extent	Forest	Forest cover	%	1990, 2006	Raster (1km)	Plutzar et al. 2015
	Arable cropland	Arable cropland cover	%	1990, 2006	Raster (1km)	Plutzar et al. 2015
	Permanent cropland	Permanent cropland cover	%	1990, 2006	Raster (1km)	Plutzar et al. 2015
	Grassland	Grassland cover	%	1990, 2006	Raster (1km)	Plutzar et al. 2015
	Built-up	Built-up cover	%	1990, 2006	Raster (1km)	Plutzar et al. 2015
	Fallow farmland	Dominantly fallow areas; including areas that were abandoned recently	Categori cal [binary]	2000-2012	Raster (250m)	Estel et al. 2015
Land-use intensity	Forestry intensity	Wood production rates	m^3 ha^{-1} yr^{-1}	1990, 2006	Raster (1km)	Verkerk et al. 2015
	Cropland intensity – Input	Fertilizer application rates [kg/ha]; <50 kg/ha, 50-150 kg/ha, >150 kg/ha	Categori cal [binary]	Quasi* 1990, 2006	Raster (1km)	Temme and Verburg 2011
	Arable cropland intensity – Output	Arable cropland yields, i.e. HANPP harvest for arable croplands	gC m^{-2} yr^{-1}	1990, 2006	Raster (1km)	Plutzar et al. 2015
	Permanent cropland intensity – Output	Permanent cropland yields, i.e. HANPP harvest for permanent crop	gC m^{-2} yr^{-1}	1990, 2006	Raster (1km)	Plutzar et al. 2015
	Grassland intensity – Input	Stocking density with cattle, sheep and goats (LSU); <25 LSU/km^2, 25-100 LSU/km^2, >100 LSU/km^2	Categori cal [binary]	1990, 2006	Raster (1km)	Neumann et al. 2009
	Grassland intensity – Output	Grassland yields, i.e. HANPP harvest for grasslands	gC m^{-2} yr^{-1}	1990, 2006	Raster (1km)	Plutzar et al. 2015

* For Latvia (LV), Lithuania (LT), Estonia (EE), Czech Republic (CZ), Slovenia (SI), and Slovakia (SK), no data was available for the year 1990. Data were obtained for the years 1991 (LV, LT, EE), 1994 (CZ, SK), and 1996 (SI) and merged with the original data for 1990 for the remaining EU27 countries.

Table SI V-2: Location factors and underlying drivers of land-system changes with pan-European coverage.

	Indicator	Category	Short description	Unit	Time	Reso-lution	Source
Location factors	Accessibility	Location	Travel time to major cities of more than 50k inhabitant	min	2000	Raster (1km)	Nelson 2008
	Aridity index	Location	Ratio of Mean Annual Precipitation & Mean Annual Potential Evapotranspiration	●	1950-2000	Raster (1km)	Metzger et al. 2013
	Environmental Zones	Location	13 Environmental Zones*	Cate-gorical [binary]	2000	Raster (1km)	Metzger et al. 2005a
	Growing degree days	Location	Sum of mean monthly temperature (if $\mu > 0$ °C) times the total # of days in those months	#	1950-2000	Raster (1km)	Metzger et al. 2013
	Population density	Demography	Number of persons per square kilometre	Pers. km^{-2}	1990, 2006	Raster (1km)	Bright et al. 2008
	Soil organic carbon	Location	Soil organic carbon content	$tC\ ha^{-1}$	2010	Raster (1km)	Lugato et al. 2014a, Lugato et al. 2014b, Panagos et al. 2012
	Terrain ruggedness	Location	Topographic hetero-geneity based on ele-vation changes between adjacent raster pixels	m	2000	Raster (1km)	Own calc. based on Riley et al. 1999
Underlying drivers	Capital input	Farm features	Total monetary inputs (crop- & livestock-specific inputs, farming overhead, depreciation, external factors)	€	2006	NUTS3	EC 2012
	Economic activity	Socio-economy	Measured as index combining GDP per capita, population density, and land cover	€ km^{-2}	2001	Raster (1km)	Metzger et al. 2010
	Economic size	Farm features	Economic size of farms expressed as Economic Size Units (1 ESU=1,200 €)	ESU	2006	NUTS3	EC 2012
	Labour input	Economy	Total labour input (as annual working units)	AWU	2006	NUTS3	EC 2012
	Land	Farm features	Total Utilised Agricultural Area (owner occupation or rented for >= 1 year)	ha	2006	NUTS3	EC 2012
	Protected areas	Institutional	Area changes in protected areas (CDDA and Natura2000)	Cate-gorical [binary]	1990, 2006	Raster (1km)	EEA 2011, EEA 2013
	Subsidies	Institutional	Subsidies on current operations linked to production (not investments)	€	2006	NUTS3	EC 2012

* The Environmental Zones are: (1) Alpine North [ALN], (2) Boreal [BOR], (3) Nemoral [NEM], (4) Atlantic North [ATN], (5) Alpine South [ALS], (6) Continental [CON], (7) Atlantic Central [ATC], (8) Pannonian [PAN], (9) Lusitanian [LUS], (10) Anatolian [ANA], (11) Mediterranean Mountains [MDM], (12) Mediterranean North [MDN], (13) Mediterranean South [MDS]

Table SI V-3: Descriptive statistics for indicators of land-use extent and land-use intensity (target year 2006 and target period 1990 to 2006).

Indicator	Unit	2006		Δ1990-2006	
		Mean	*SD*	*Mean*	*SD*
Cropland arable	%	23.95	26.04	-3.05	5.95
Cropland permanent	%	3.27	8.73	-0.38	1.83
Fallow farmland	%	3.38	7.37	---	---
Grassland	%	28.64	23.55	1.60	9.39
Forest	%	40.42	32.83	1.67	6.05
Built-up	%	2.78	5.87	0.34	1.19
Low livestock density	%	7.64	14.02	0.86	5.04
Medium livestock density	%	6.12	15.40	0.25	8.07
High livestock density	%	1.94	7.20	-1.10	6.18
Low nitrogen input	%	7.38	18.22	0.80	13.07
Medium nitrogen input	%	15.07	26.92	-0.78	17.36
High nitrogen input	%	9.46	22.54	-0.03	12.73
HANPP harv arable	gC m^{-2} yr^{-1}	347.03	275.77	18.14	129.33
HANPP harv permanent	gC m^{-2} yr^{-1}	39.50	75.65	8.83	54.97
HANPP harv grassland	gC m^{-2} yr^{-1}	79.94	85.44	-6.21	46.37
Forest harvesting	m^3 ha^{-1} yr^{-1}	1.08	1.43	0.23	0.58

Table SI V-4: Descriptive statistics for all continuously scaled explanatory factors. Environmental Zones (EnvZ) and Protected Areas (PA) were not included due to their categorical data type.

Indicator	Unit	Mean	Median	SD
Accessibility	min	144.96	94.44	158.64
Aridity Index	●	1.02	0.96	0.48
Economic activity	€ km^{-2}	2246860.88	245872.12	14571976.18
Growing degree days	#	34190.42	32739.11	12418.85
Population density	pers. km^{-2}	114.30	13.13	528.29
Economic size	ESU (€)	54.33	39.70	53.75
Labour input	AWU	2.25	1.70	2.70
UAAR	ha	81.28	50.57	110.61
Capital input	€	114687.08	84959.20	143037.92
Subsidies	€	29134.79	20437.16	32794.93
Soil organic carbon	tC ha^{-1}	84.68	66.72	88.84
Terrain ruggedness	m	36.81	17.56	50.80

Table SI V-5: Cross-tabulation of the spatial overlay in square kilometres of each Land-System Archetype (LSA) and Archetypical Change Trajectory (ACT).

	LSA01	LSA02	LSA03	LSA04	LSA05	LSA06	LSA07	LSA08
ACT01	29,358	81	5,715	6,237	729	504	621	891
ACT02	2,232	8,739	24,039	14,985	4,059	2,970	6,147	17,973
ACT03	2,754	486	53,127	3,870	279	252	45	324
ACT04	342	1,944	252	37,674	4,248	1,368	0	18
ACT05	144	4,779	5,571	4,761	2,457	6,966	1,926	9,765
ACT06	468	747	2,034	48,033	4,887	2,268	45	414
ACT07	504	990	306	2,745	81,711	4,563	135	846
ACT08	1,152	1,611	14,382	68,706	24,507	10,683	1,899	5,031
ACT09	819	621	1,827	4,860	1,935	4,005	7,128	46,260
ACT10	468	2,088	1,647	4,455	1,917	3,321	0	3,483
ACT11	459	9	2,097	891	198	14,049	1,773	783
ACT12	1,170	5,922	2,943	5,508	6,066	22,428	2,187	12,969
ACT13	72	11,862	1,206	1,449	3,195	1,827	207	2,340
ACT14	6,219	6,462	54,432	140,742	66,978	13,797	567	10,458
ACT15	45	43,632	180	1,017	4,365	351	108	612
ACT16	2,790	11,169	4,581	7,164	4,014	3,510	1,449	2,367
ACT17	6,273	57,384	143,352	148,707	47,952	73,548	15,066	54,495

	LSA09	LSA10	LSA11	LSA12	LSA13	LSA14	LSA15
ACT01	1,458	288	3,555	171	8,325	13,446	1,422
ACT02	13,482	8,640	15,624	13,806	25,974	38,889	3,231
ACT03	549	144	387	18	4,581	4,554	720
ACT04	639	2,322	171	279	828	5,517	162
ACT05	11,385	17,226	19,683	28,215	6,165	24,849	2,313
ACT06	1,395	702	315	405	3,474	6,165	432
ACT07	1,071	1,791	27	171	954	2,547	288
ACT08	27,342	4,311	17,415	12,735	8,163	50,652	3,051
ACT09	3,159	1,404	1,251	351	20,124	5,418	234
ACT10	40,950	2,142	882	207	6,705	4,563	261
ACT11	12,366	261	164,862	9,747	6,741	26,712	432
ACT12	21,492	80,217	24,147	138,249	3,996	44,163	396
ACT13	3,204	17,226	3,078	4,509	1,278	5,319	198
ACT14	24,867	45,693	3,663	14,085	11,745	73,035	3,375
ACT15	4,257	9,135	216	4,986	369	5,679	657
ACT16	8,712	4,536	1,989	1,539	18,630	16,785	40,365
ACT17	72,495	193,689	94,653	588,519	63,513	158,823	18,657

Table SI V-6: De-standardised indicator values for all LSAs.

Indicator	Unit	LSA01	LSA02	LSA03	LSA04	LSA05	LSA06	LSA07	LSA08
Cropland arable	%	38.63	13.84	64.31	57.88	50.11	14.17	17.68	20.68
Cropland permanent	%	2.66	40.91	1.73	1.95	3.38	1.44	1.67	1.38
Fallow farmland	%	3.66	1.81	1.17	1.93	2.67	32.22	2.26	1.98
Grassland	%	23.30	27.99	16.67	22.66	29.08	33.98	66.86	61.84
Forest	%	29.78	18.54	10.34	10.19	13.89	45.15	10.30	14.41
Built-up	%	3.89	3.59	2.87	2.69	2.03	1.77	3.40	1.82
Low livestock dens.	%	8.82	8.69	3.12	3.32	5.94	10.20	2.63	6.62
Medium livestock dens.	%	5.28	4.56	3.43	2.84	3.65	4.32	11.13	67.45
High livestock dens.	%	2.39	1.25	1.08	1.11	1.14	1.02	69.98	2.12
Low nitrogen input	%	6.10	11.41	1.94	3.93	67.41	5.17	2.46	2.93
Medium nitrogen input	%	30.16	7.90	3.95	77.56	6.31	8.56	3.74	5.54
High nitrogen input	%	14.95	3.34	79.43	3.00	1.54	1.42	5.89	5.44
HANPP_harv arable	gC m^{-2} yr^{-1}	567.78	360.03	613.45	436.96	350.69	199.14	517.09	481.01
HANPP_harv perm	gC m^{-2} yr^{-1}	472.66	64.68	51.85	45.06	39.74	15.63	43.61	33.26
HANPP_harv grass	gC m^{-2} yr^{-1}	88.51	48.13	88.79	62.66	70.31	70.52	285.77	253.26
Forest harvesting	m^3 ha^{-1} yr^{-1}	1.31	0.18	0.38	0.27	0.28	1.15	0.55	0.45

Indicator	Unit	LSA09	LSA10	LSA11	LSA12	LSA13	LSA14	LSA15
Cropland arable	%	19.39	6.27	3.99	2.85	35.09	18.72	16.98
Cropland permanent	%	2.09	1.98	1.04	1.45	1.39	1.62	2.49
Fallow farmland	%	4.35	2.09	2.32	1.66	2.04	4.09	1.54
Grassland	%	42.38	70.86	12.02	13.08	36.13	23.76	14.93
Forest	%	34.67	36.21	82.14	78.32	18.51	49.23	9.15
Built-up	%	2.10	1.51	1.47	1.08	4.65	2.59	39.31
Low livestock dens.	%	49.10	4.13	5.08	1.78	10.47	9.07	4.22
Medium livestock dens.	%	5.06	3.41	1.85	1.16	17.07	3.31	2.07
High livestock dens.	%	1.11	1.04	1.08	1.00	4.38	1.06	1.37
Low nitrogen input	%	3.65	3.96	1.28	1.72	3.64	4.05	3.29
Medium nitrogen input	%	8.25	4.37	2.71	1.67	14.61	14.19	7.25
High nitrogen input	%	3.69	1.18	2.82	1.09	21.24	4.62	5.46
HANPP_harv arable	gC m^{-2} yr^{-1}	380.09	152.12	316.23	75.82	748.94	449.50	453.84
HANPP_harv perm	gC m^{-2} yr^{-1}	30.83	14.94	11.87	10.91	92.93	41.19	45.32
HANPP_harv grass	gC m^{-2} yr^{-1}	141.28	61.65	64.79	19.16	217.53	66.48	87.48
Forest harvesting	m^3 ha^{-1} yr^{-1}	1.01	0.30	4.67	1.15	0.81	1.42	0.34

Table SI V-7: De-standardised indicator values for all ACTs.

Indicator	Unit	ACT01	ACT02	ACT03	ACT04	ACT05	ACT06	ACT07	ACT08	ACT09
Δ Cropland arable	%	-3.15	-0.81	-6.07	-8.16	-2.02	-6.49	-7.64	-7.79	-1.73
Δ Cropland permanent	%	-0.04	-0.23	-0.03	-0.30	-0.19	-0.19	-0.36	-0.27	-0.14
Δ Grassland	%	2.27	-0.33	5.56	8.88	0.11	5.83	7.33	7.73	0.58
Δ Forest	%	0.56	1.31	0.11	0.66	1.69	0.78	1.10	1.21	1.26
Δ Built-up	%	0.47	0.28	0.26	0.18	0.30	0.24	0.28	0.27	0.37
Δ Low livestock dens.	%	0.56	0.41	0.53	0.27	0.09	0.38	0.49	0.25	0.08
Δ Medium livestock dens.	%	-0.34	0.17	-0.35	-0.09	0.10	-0.21	-0.28	0.27	34.77
Δ High livestock dens.	%	-0.23	-0.53	-0.18	-0.18	-0.18	-0.16	-0.19	-0.51	-34.62
Δ Low nitrogen input	%	0.26	0.05	-4.17	-56.66	0.16	5.75	59.34	-0.77	0.21
Δ Medium nitrogen input	%	-1.11	-0.94	-55.46	57.16	-0.08	57.26	-58.12	0.56	-0.58
Δ High nitrogen input	%	0.86	0.88	59.73	-0.47	-0.11	-63.05	-0.82	0.37	0.34
Δ HANPP_ harv arable	gC m^{-2} yr^{-1}	37.98	311.25	28.50	27.70	-290.27	15.32	3.29	-40.64	47.47
Δ HANPP_ harv perm	gC m^{-2} yr^{-1}	275.63	8.92	9.87	8.00	-5.84	-7.51	7.73	12.55	5.93
Δ HANPP_ harv grass	gC m^{-2} yr^{-1}	8.64	3.45	-15.24	-12.27	-1.09	-0.11	-12.93	-111.33	-12.99
Δ Forest harvesting	m^3 ha^{-1} yr^{-1}	0.42	0.15	0.11	0.08	0.32	0.08	0.08	0.28	0.19

Indicator	Unit	ACT10	ACT11	ACT12	ACT13	ACT14	ACT15	ACT16	ACT17
Δ Cropland arable	%	-2.97	-0.78	-1.32	2.17	-11.43	-5.68	-4.13	-0.41
Δ Cropland permanent	%	-0.04	0.00	-0.36	1.96	-0.57	-10.42	-0.93	-0.12
Δ Grassland	%	1.06	-1.25	-10.52	8.68	13.11	12.39	-2.36	-0.20
Δ Forest	%	0.77	1.70	10.80	-24.74	1.85	5.74	-0.28	0.53
Δ Built-up	%	0.34	0.09	0.05	0.41	0.29	0.68	5.20	0.11
Δ Low livestock dens.	%	33.22	0.35	0.10	0.75	0.38	0.50	0.45	0.14
Δ Medium livestock dens.	%	-32.83	-0.09	-0.05	-0.59	-0.26	-0.43	0.28	0.05
Δ High livestock dens.	%	-0.29	-0.24	-0.04	-0.13	-0.12	-0.04	-0.72	-0.20
Δ Low nitrogen input	%	0.46	-0.15	0.07	-1.48	1.32	0.49	0.65	-0.07
Δ Medium nitrogen input	%	-0.11	0.00	-0.18	1.17	-1.55	-0.44	-0.56	-0.16
Δ High nitrogen input	%	-0.57	0.08	0.19	0.25	0.37	-0.03	-0.06	0.19
Δ HANPP_ harv arable	gC m^{-2} yr^{-1}	27.43	28.19	-0.44	6.84	22.50	105.25	25.13	17.40
Δ HANPP_ harv perm	gC m^{-2} yr^{-1}	18.18	-3.20	6.93	6.20	15.83	17.29	8.43	-6.01
Δ HANPP_ harv grass	gC m^{-2} yr^{-1}	-15.21	0.04	0.24	27.95	2.26	9.55	-5.89	0.53
Δ Forest harvesting	m^3 ha^{-1} yr^{-1}	0.30	1.82	0.17	-0.49	0.09	0.04	0.04	0.16

Figure SI V-1: SOM performance plots for LSAs (a) and ACTs (b) with different output grid dimensionalities and U-matrices for LSAs (c) and ACTs (d). Low Davies-Bouldin (DB) index values represent low intra- and high inter-cluster variability indicating a mathematically more satisfactory clustering result. Mean distances were calculated for all pixels based on the Euclidean distance to their respective cluster centroid value. We selected 16 clusters and a 4x4 dimensionality (LSAs) and 20 clusters and a 5x4 dimensionality (ACTs) based on the location of optimal DB index and mean distance values. For LSAs, mean deviance was levelling off at 16 clusters despite an optimal DB values at 12 clusters. U-matrices for LSAs (c) and ACTs (d) indicate each cluster's similarity to its topological neighbours with lower values representing a higher degree of similarity.

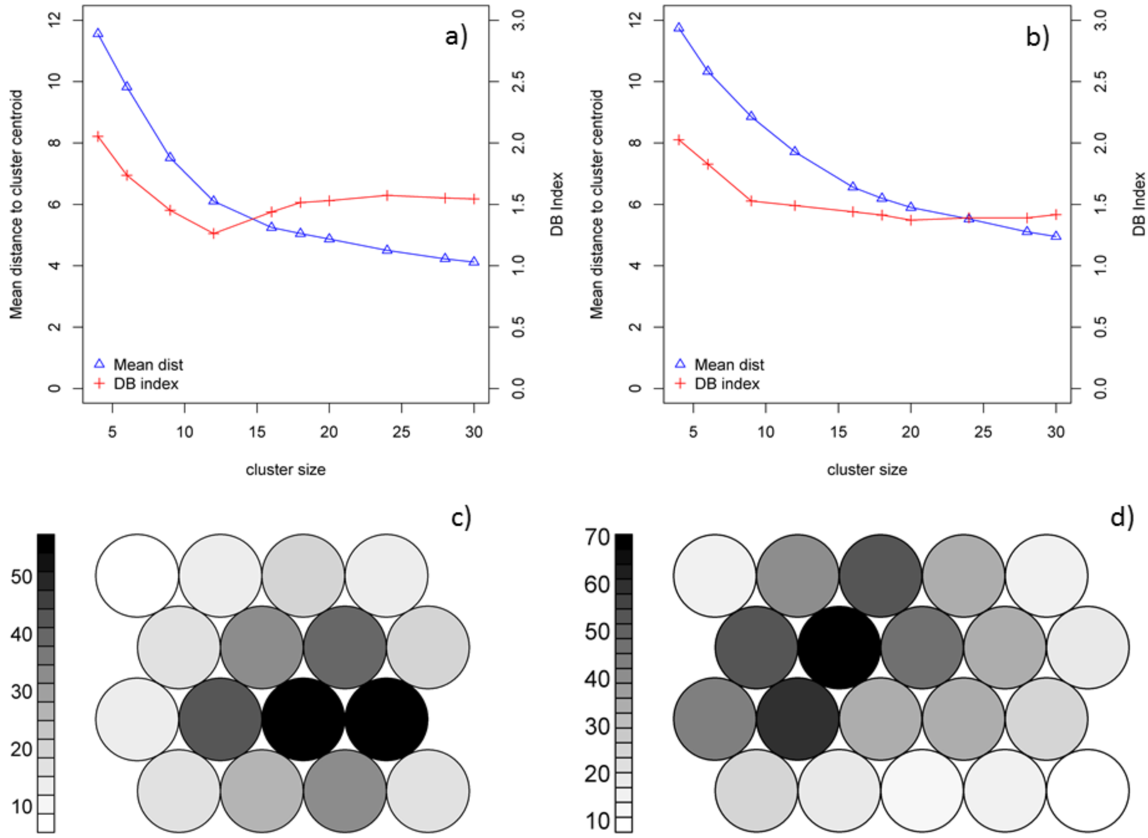


Figure SI V-2: Boxplot panel for all continuously-scaled explanatory factors per Land-System Archetype. Red horizontal lines indicate the mean value of all LSA medians (solid) and means (dotted). Note that the values for “economic activity” are log-scaled.

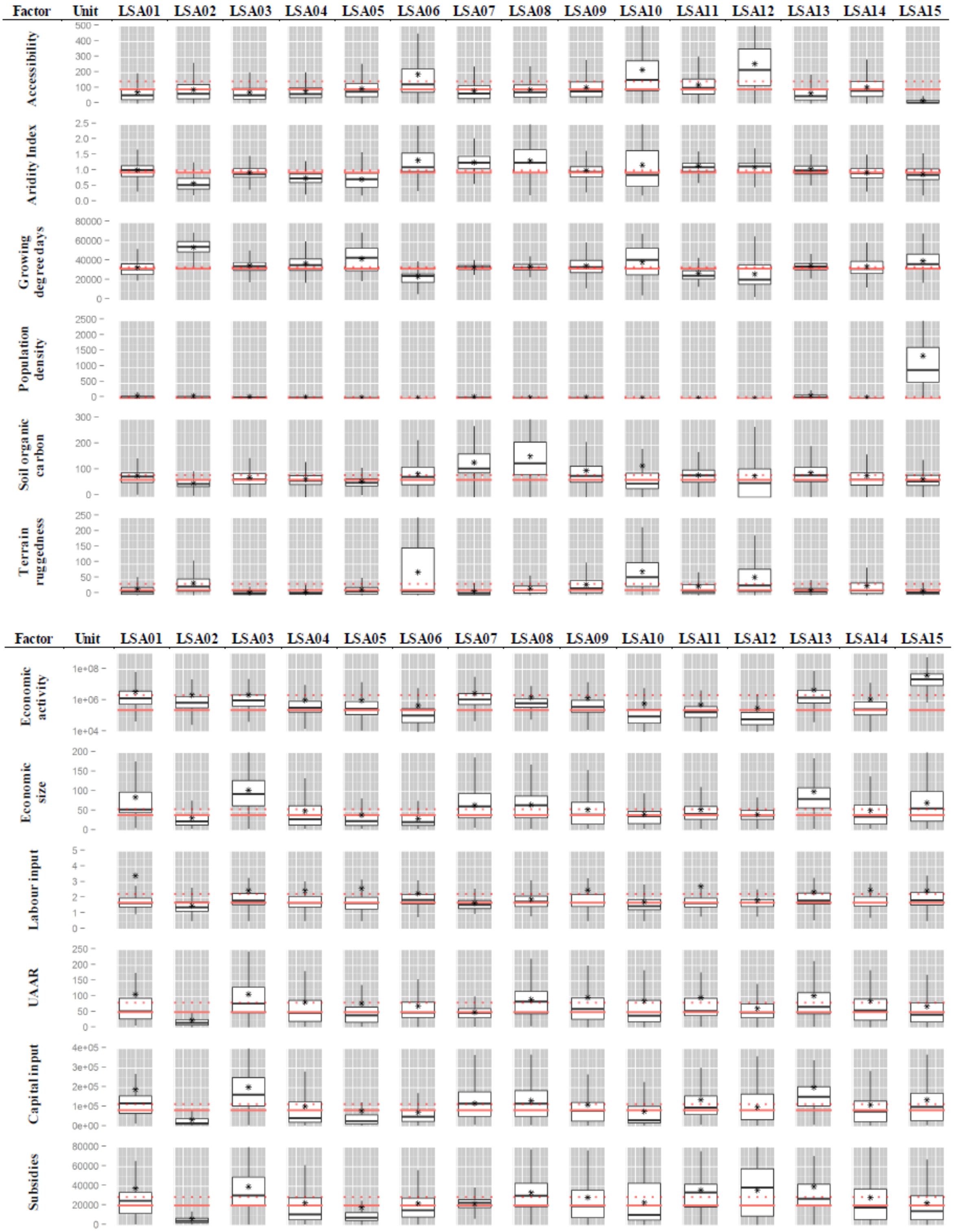


Figure SI V-3: Boxplot panel for all continuously-scaled explanatory factors per Archetypical Change Trajectory. Red horizontal lines indicate the mean value of all ACT medians (solid) and means (dotted). Note that the values for "economic activity" are log-scaled.

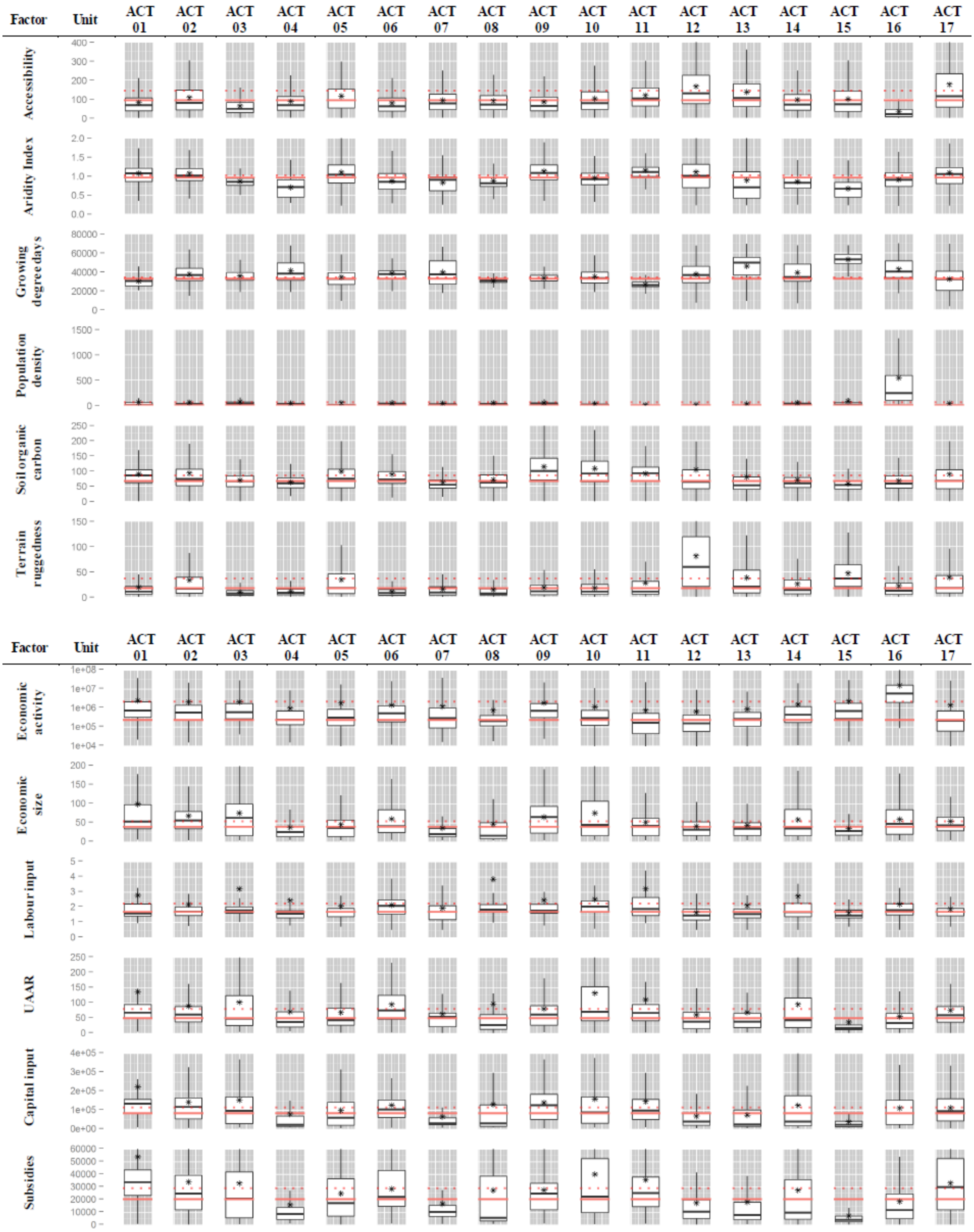


Figure SI V-4: Spatial co-occurrence of Environmental Zones with LSAs (top) and ACTs (bottom). The Environmental Zones are: (1) Alpine North [ALN], (2) Boreal [BOR], (3) Nemoral [NEM], (4) Atlantic North [ATN], (5) Alpine South [ALS], (6) Continental [CON], (7) Atlantic Central [ATC], (8) Pannonian [PAN], (9) Lusitanian [LUS], (10) Anatolian [ANA], (11) Mediterranean Mountains [MDM], (12) Mediterranean North [MDN], (13) Mediterranean South [MDS]. The legend provides a general overview of the magnitude of spatial overlaps between LSAs/ACTs and the Environmental Zones. Values sum up row-wise to 100% and legend bubble sizes provide categorical information of the continuously scaled magnitude of spatial overlay.

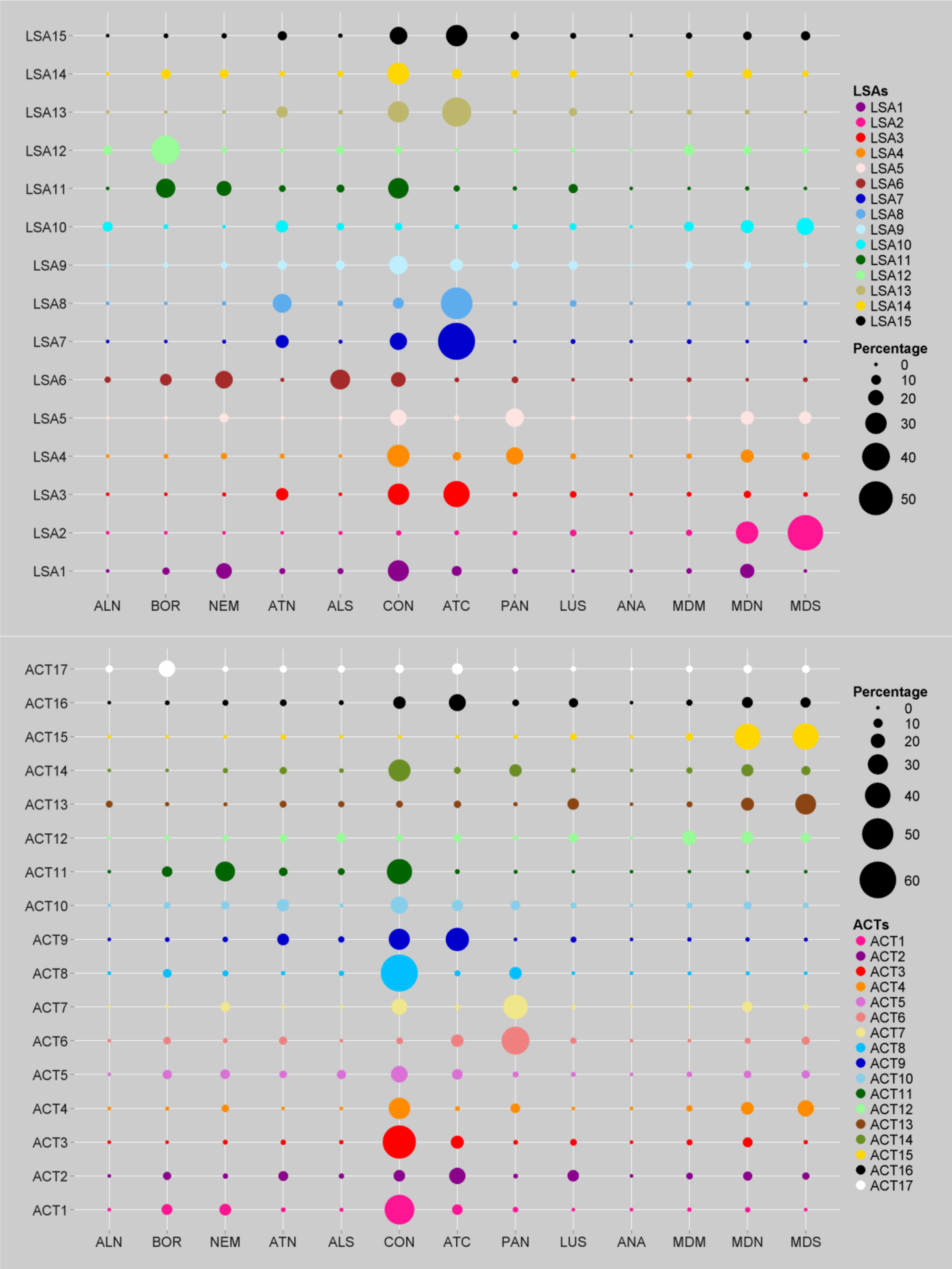
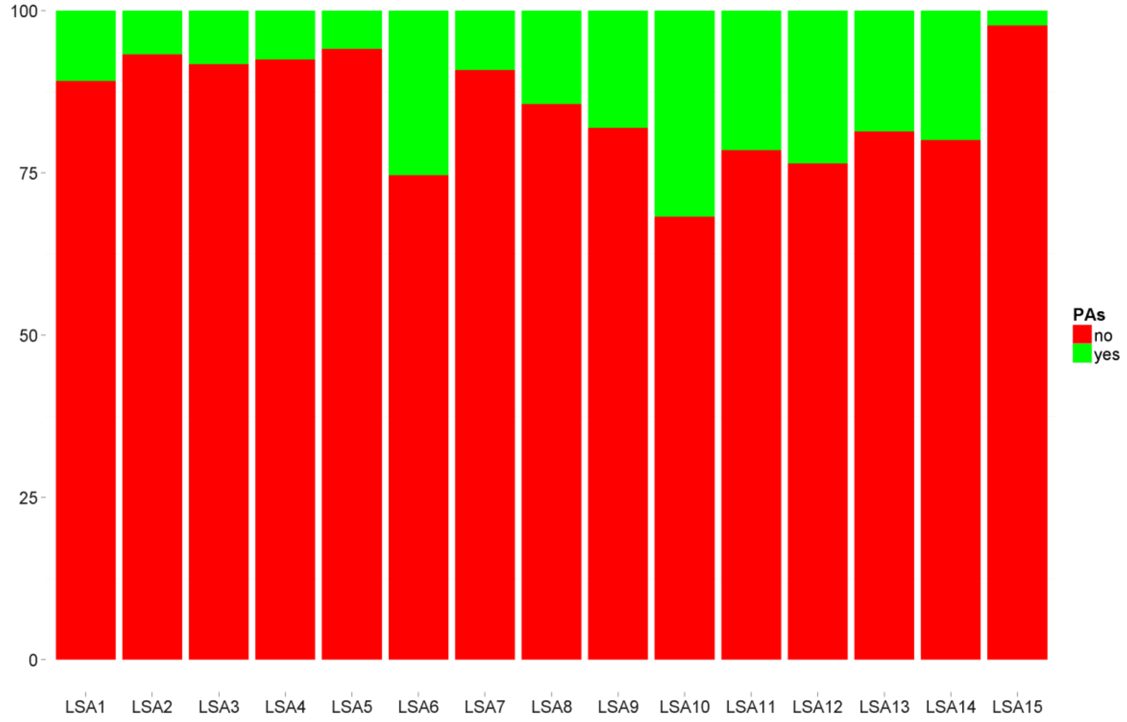


Figure SI V-5: Spatial co-occurrence of Protected Areas with LSAs (top) and ACTs (bottom).



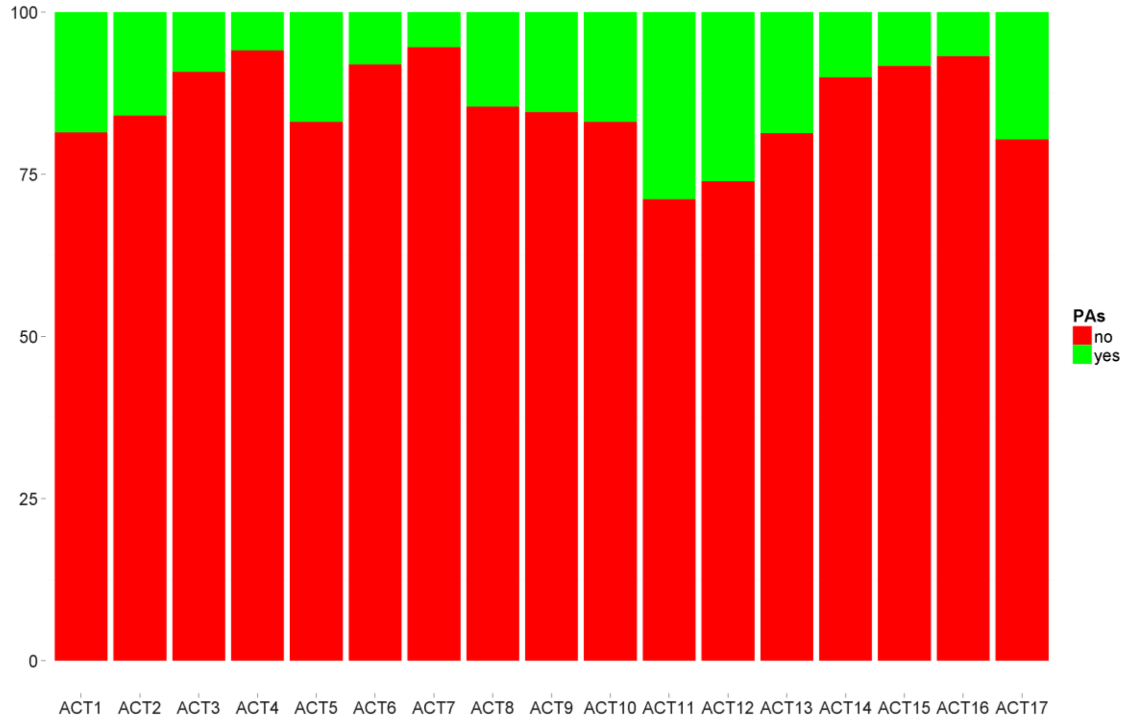


Figure SI V-6: Maps of Euclidean distances for each grid cell of the LSA (left) and ACT (right) assessment to its corresponding cluster centroid. Larger deviations indicate that assigned SOM clusters were not optimal to represent the contained grid cells.

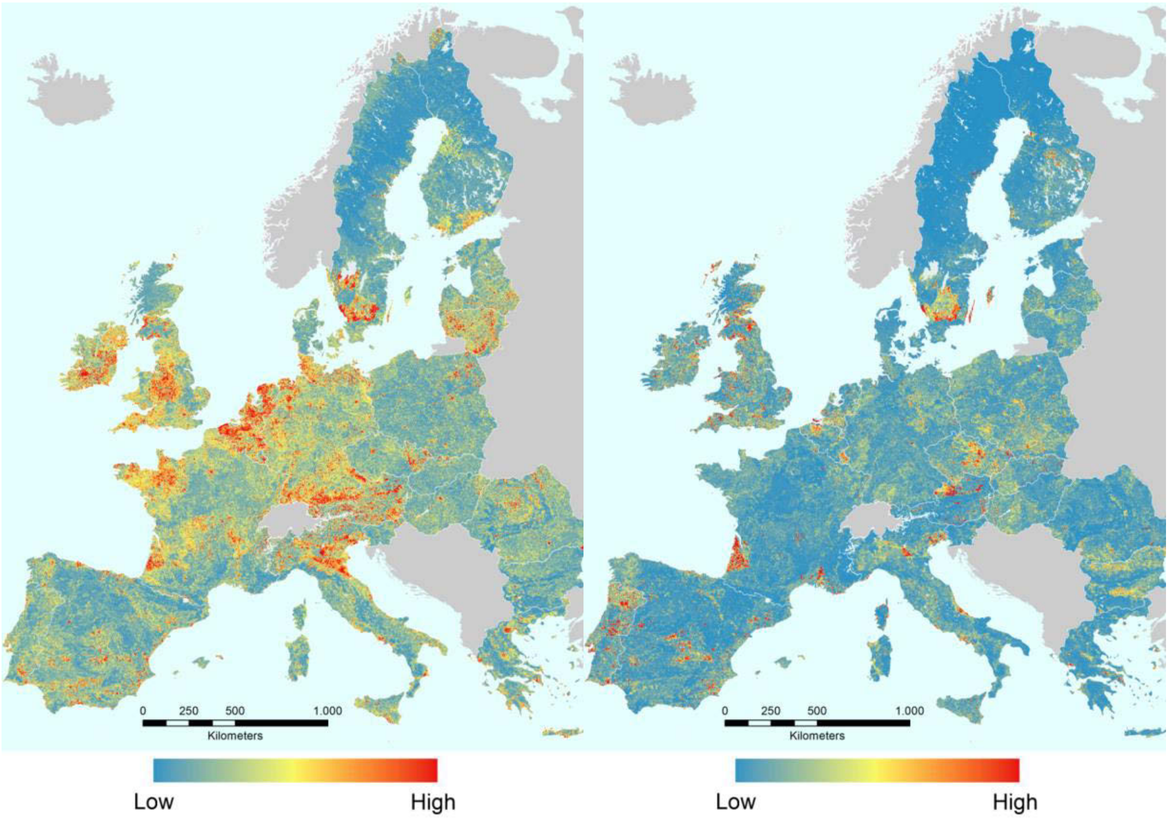
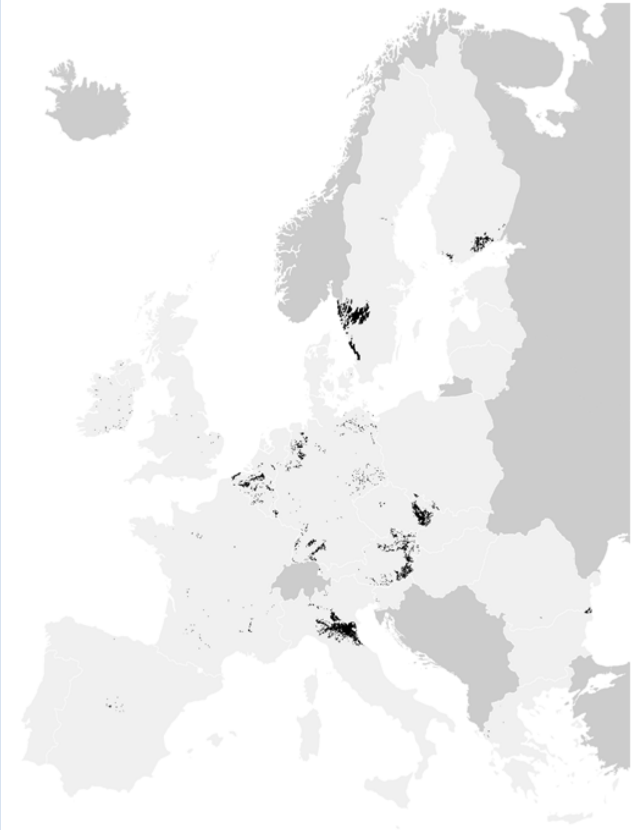
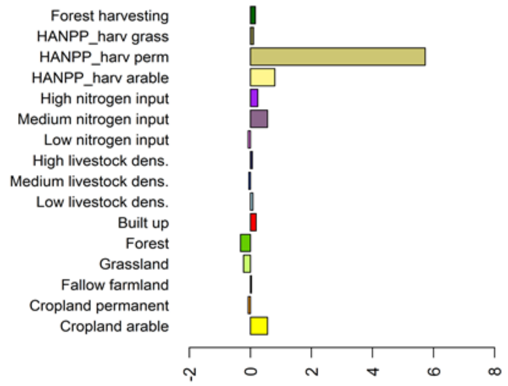


Figure SI V-7: Detailed descriptions of LSA01 to LSA 15.

LSA01: High-intensity cropland



Archetype characterisation

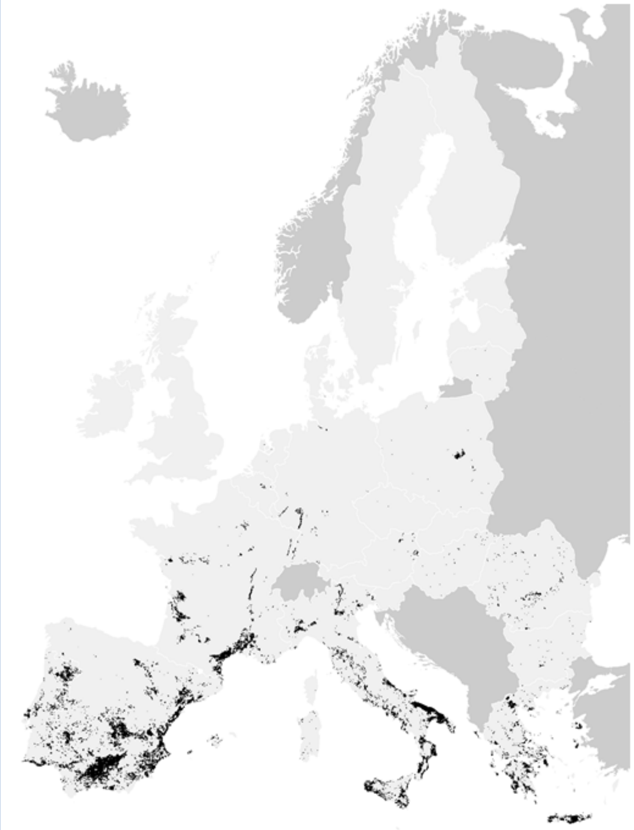


Archetype description

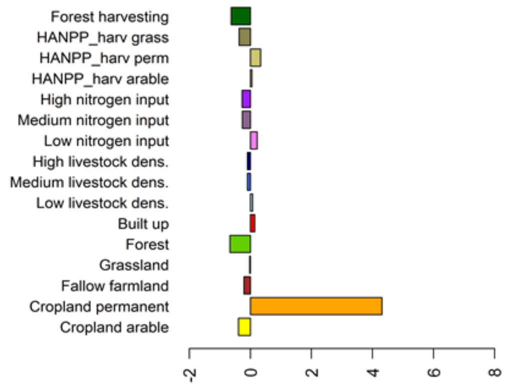
This archetype is dominated by very high yields of permanent crops (473 gC m^{-2} yr^{-1}; μ = 39 gC m^{-2} yr^{-1}) and by high arable cropland cover (39 %; μ = 24 %) and yields (568; μ = 347gC m^{-2} yr^{-1}). Arable cropland is intensively managed with substantial medium (30 %; μ = 15 %) and high (15 %; μ = 9 %) nitrogen input. Forest (30%; μ = 40 %) and grassland (23%; μ = 29 %) cover revealed low values while urban built-up was slightly above average (4 %; μ = 3 %). All other values did not deviate much from their aggregate mean values, in particular permanent cropland cover (μ = 3%).

Areas belonging to this archetype are very intensively managed croplands with high yielding permanent crops (assumingly on small areas) with impacts of settlements.

LSA02: Large-scale permanent cropland



Archetype characterisation

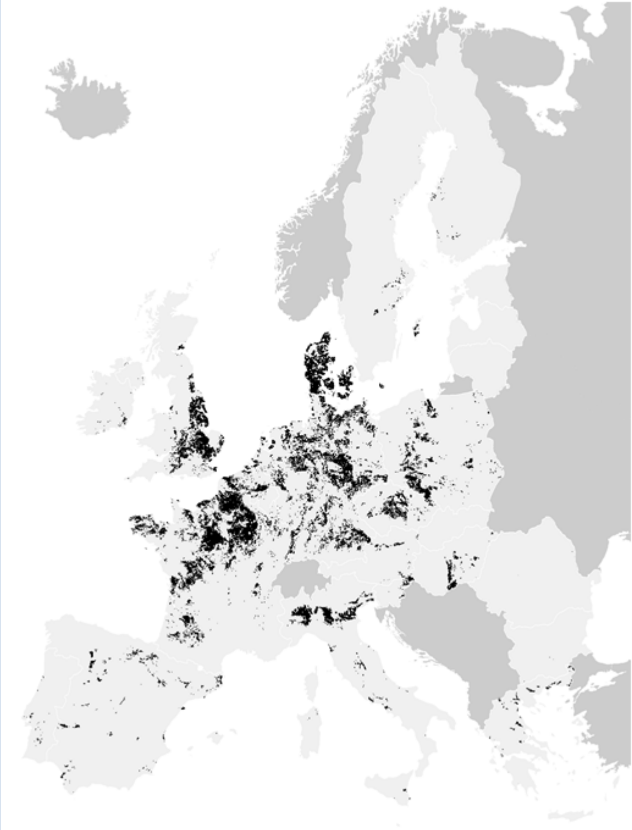


Archetype description

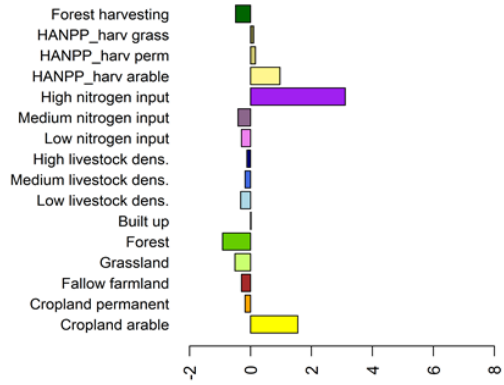
This archetype is dominated by very high permanent cropland cover (41 %; μ = 3 %) and high permanent cropland yields (65 gC m^{-2} yr^{-1}; μ = 39 gC m^{-2} yr^{-1}). Arable cropland (14 %; μ = 24 %), fallow farmland (2 %; μ = 3 %), and forest (18 %; μ = 40 %) revealed low coverages. Arable croplands were not intensively managed (low nitrogen input, 11 %; μ = 7 %) with yields close to the aggregate mean (μ = 347 gC m^{-2} yr^{-1}). Forest harvesting (0.18 m^3 ha^{-1} yr^{-1}; μ = 1.08 m^3 ha^{-1} yr^{-1}) and grassland yields (48 gC m^{-2} yr^{-1}; μ = 80 gC m^{-2} yr^{-1}) were very low. All other values did not deviate much from their aggregate mean values.

Areas belonging to this archetype are highly specialised on permanent crop production and only marginally shaped by other (then low-intensity) land uses.

LSA03: High-intensity arable cropland



Archetype characterisation

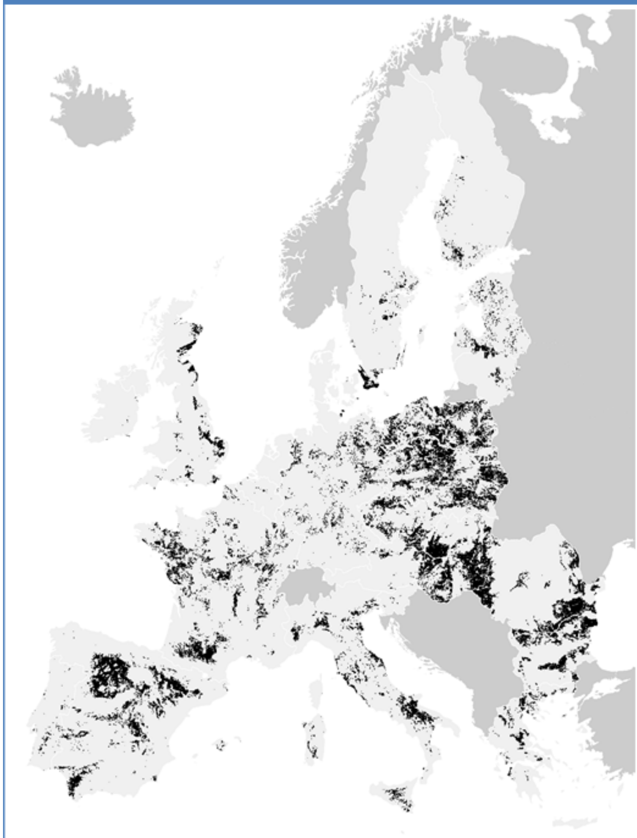


Archetype description

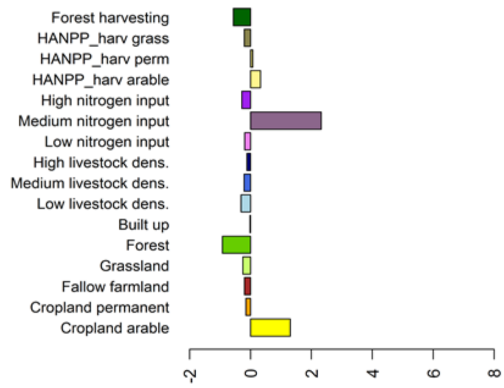
This archetype is dominated by very high arable cropland cover (64 %; μ = 24 %), yields (613 gC m^{-2} yr^{-1}; μ = 347 gC m^{-2} yr^{-1}), and nitrogen input (79 %; μ = 9 %). Built-up areas (μ = 3 %) as well as grassland (μ = 80 gC m^{-2} yr^{-1}) and permanent cropland (μ = 39 gC m^{-2} yr^{-1}) yields did not deviate much from their aggregate mean values. All other indicators revealed low to very low values, especially forest cover (10 % μ = 40 %) and harvesting (0.38 m^{3} ha^{-1} yr^{-1}; μ = 1.08 m^{3} ha^{-1} yr^{-1}), grassland cover (17 %; μ = 29 %), fallow farmland (1 %; μ = 3 %), and consequently medium (4 %; μ = 15 %) and low nitrogen input (2 %; μ = 7 %).

Areas belonging to this archetype are highly specialised on arable cropland use and production with high management intensity.

LSA04: Medium-intensity arable cropland



Archetype characterisation

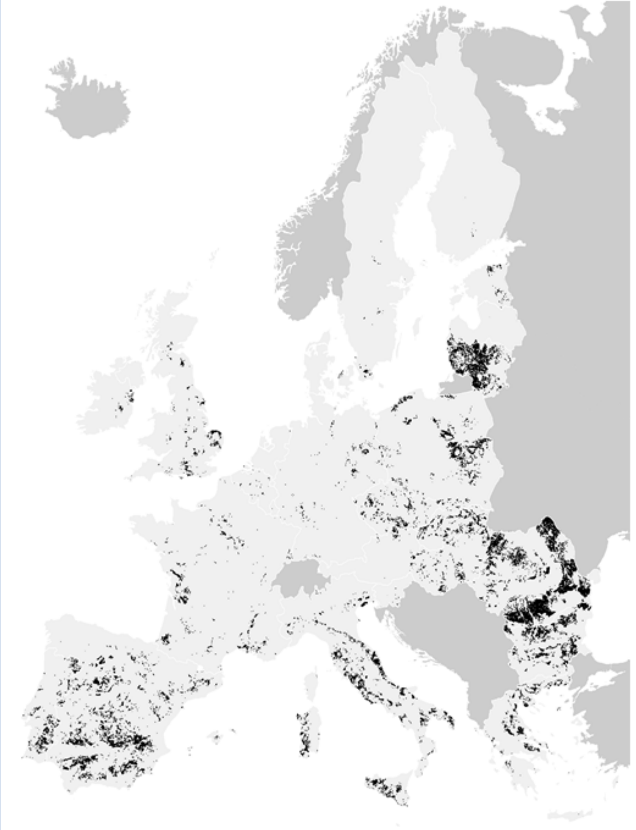


Archetype description

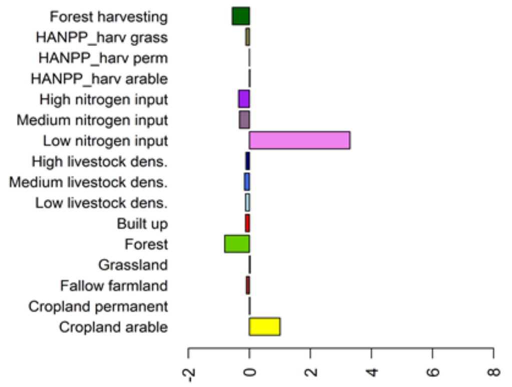
This archetype is dominated by high arable cropland cover (58 %; μ = 24 %) and yields (437 gC m^{-2} yr^{-1}; μ = 347 gC m^{-2} yr^{-1}) as well as medium nitrogen input (78 %; μ = 15 %). Built-up areas (μ = 3 %) and permanent cropland yields (μ = 39 gC m^{-2} yr^{-1}) did not deviate much from their aggregate mean values. All other indicators revealed low to very low values, especially forest cover (10 % μ = 40 %) and harvesting (0.27 m^{3} ha^{-1} yr^{-1}; μ = 1.08 m^{3} ha^{-1} yr^{-1}), grassland cover (23 %; μ = 29 %), and consequently high (3 %; μ = 9 %) and low nitrogen input (4 %; μ = 7 %).

Areas belonging to this archetype are much specialised on arable cropland use and production with medium management intensity.

LSA05: Low-intensity arable cropland



Archetype characterisation

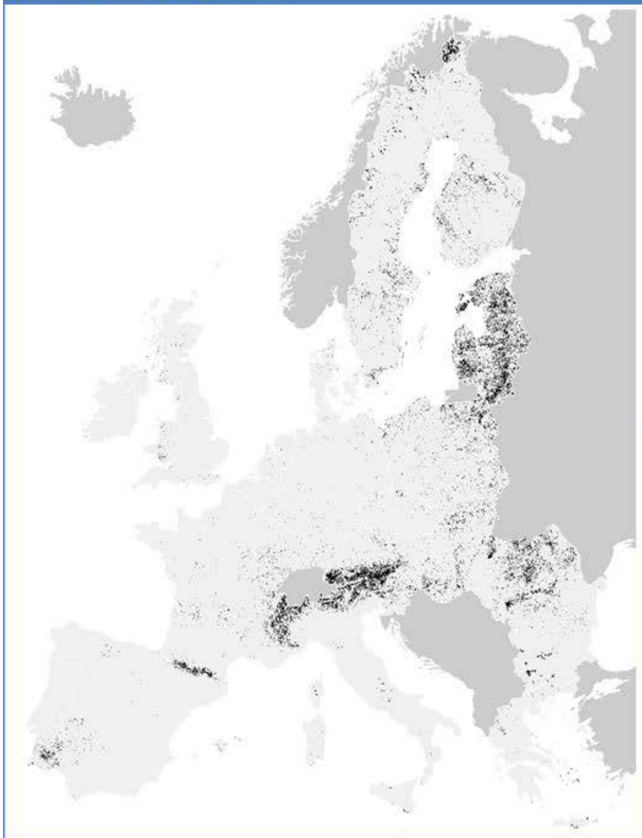


Archetype description

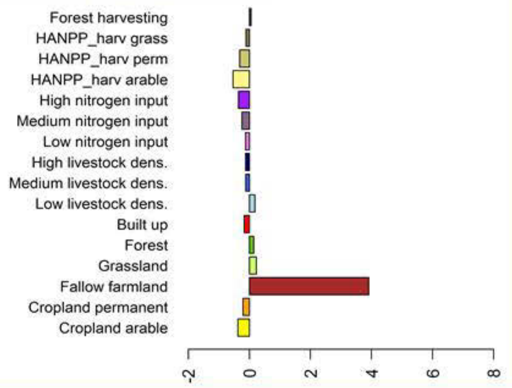
This archetype is dominated by high arable cropland cover (50 %; μ = 24 %) and low nitrogen input (67 %; μ = 7 %) with average yields (μ = 347 gC m^{-2} yr^{-1}). Forest cover (14 % μ = 40 %) and harvesting (0.28 m^3 ha^{-1} yr^{-1}; μ = 1.08 m^3 ha^{-1} yr^{-1}) as well as high (2 %; μ = 9 %) and medium nitrogen input (6 %; μ = 15 %) revealed low to very low values. All other indicators were close to their aggregate mean values.

Areas belonging to this archetype are specialised on arable cropland use with low management intensity and are likely to co-occur with other land uses without any pronounced focus. Due to yields close to the aggregate means, these areas are likely to be marginal regions where natural productivity is limited but are nevertheless suited for agriculture.

LSA06: Fallow farmland



Archetype characterisation

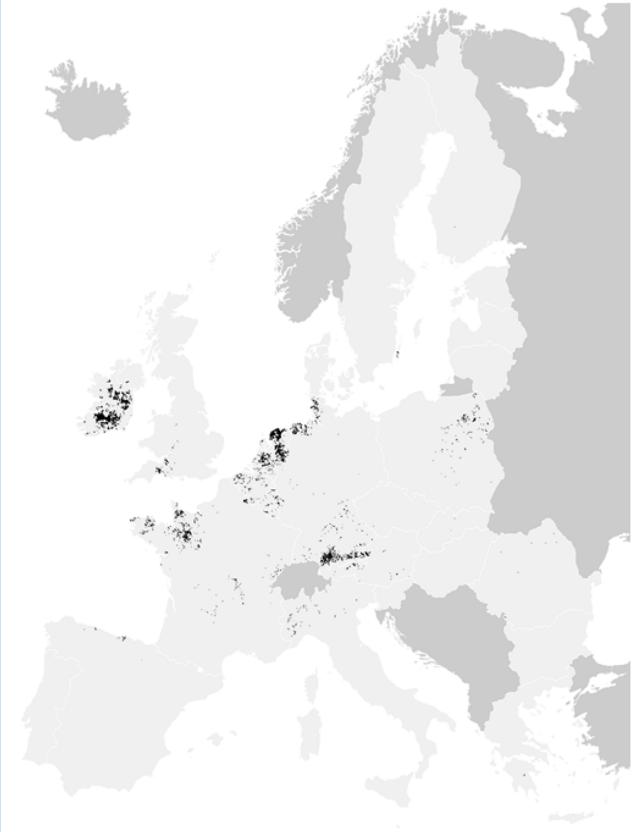


Archetype description

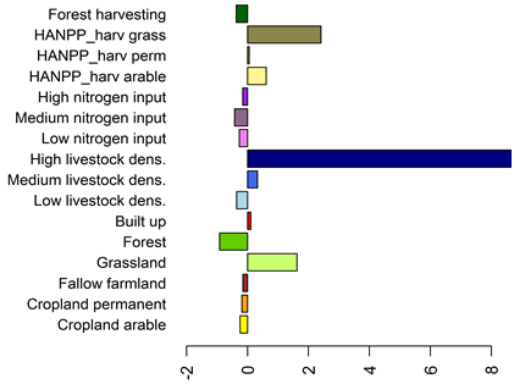
This archetype is dominated by very high fallow farmland cover (32 %; μ = 3 %) and above average forest (45 %; μ = 40 %) and grassland (34 %; μ = 29 %) cover. Existing grassland is extensively managed (low livestock density, 10 %; μ = 8 %). All other indicators were close to their aggregate mean values or disproportionally low, especially cropland cover (14 %; μ = 24 %) and yields (199 gC m^{-2} yr^{-1}; μ = 347 gC m^{-2} yr^{-1}), as well as medium (9 %; μ = 15 %) and high (1 %; μ = 9 %) nitrogen input.

Areas belonging to this archetype were taken out of agricultural use with few active croplands and low related production. These areas reveal signs of semi-natural vegetation with low management intensity.

LSA07: High-intensity livestock farming



Archetype characterisation

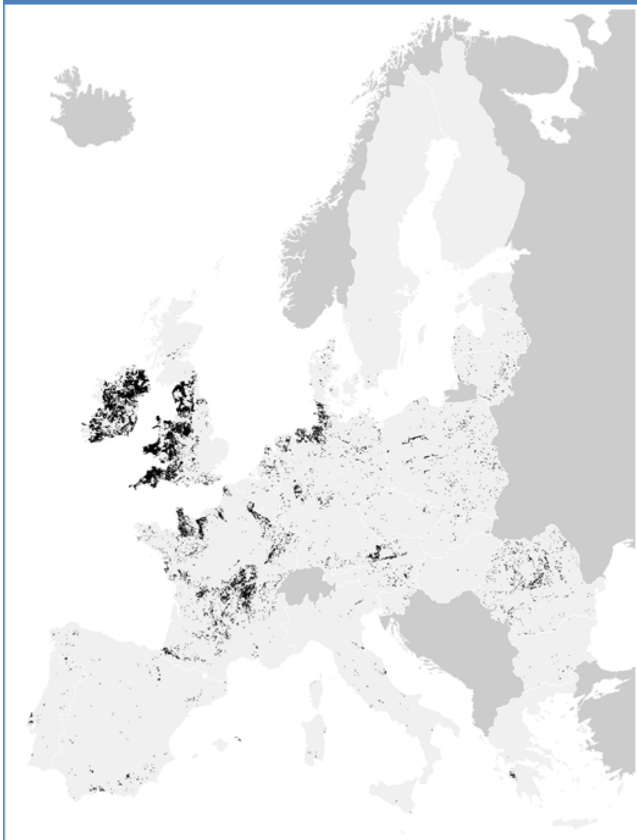


Archetype description

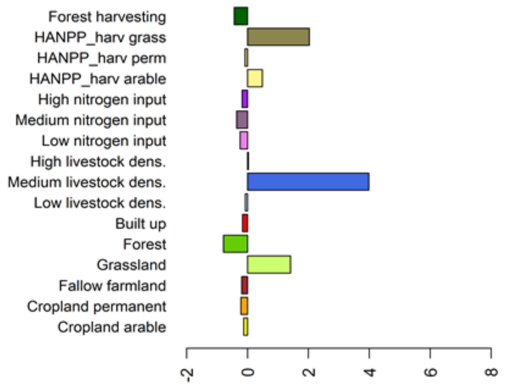
This archetype is dominated by very high grassland cover (67 %; μ = 29 %) and yields (286 gC m^{-2} yr^{-1}; μ = 80 gC m^{-2} yr^{-1}) as well as high livestock density (70 %; μ = 2 %). Despite below average arable cropland cover (18 %; μ = 24 %) and nitrogen input, arable crop yields are high (517 gC m^{-2} yr^{-1}; μ = 347 gC m^{-2} yr^{-1}). All other indicators were close to their aggregate mean values or disproportionally low, especially forest cover (10 %; μ = 40 %) and harvesting (0.55 m^3 ha^{-1} yr^{-1}; μ = 1.08 m^3 ha^{-1} yr^{-1}).

Areas belonging to this archetype show a clear specialisation on grasslands with very intensive management regarding livestock and productivity. Other land uses are only of minor importance, especially forests.

LSA08: Medium-intensity livestock farming



Archetype characterisation

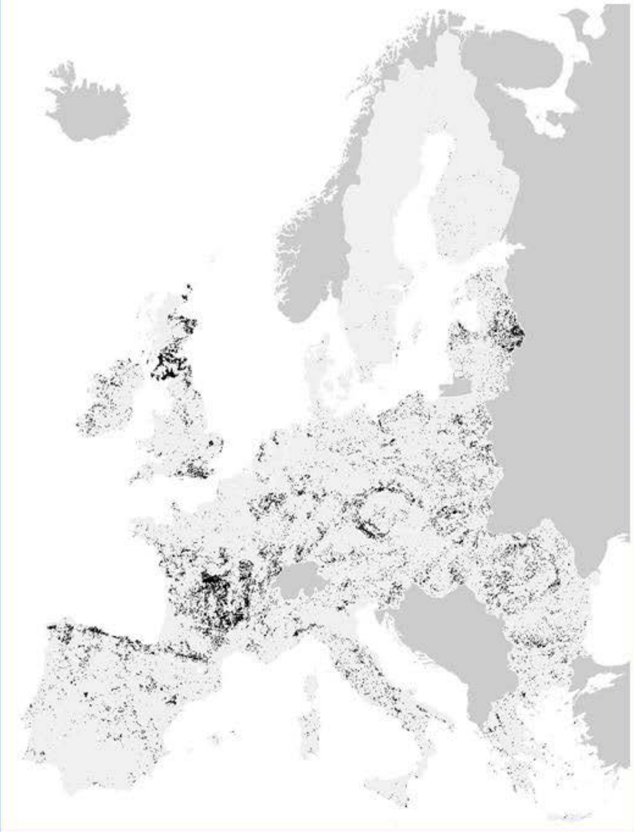


Archetype description

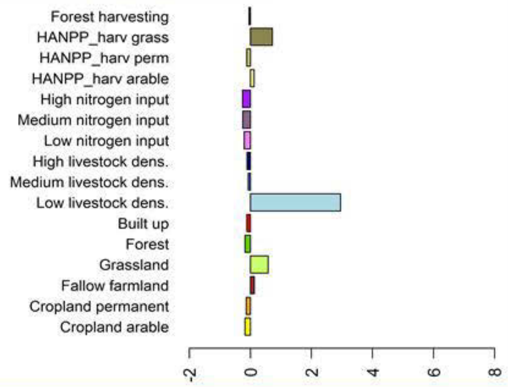
This archetype is dominated by very high grassland cover (62 %; μ = 29 %) and yields (253 gC m^{-2} yr^{-1}; μ = 80 gC m^{-2} yr^{-1}) as well as medium livestock density (67%; μ = 6 %). Despite slightly below average arable cropland cover (20 %; μ = 24 %) and nitrogen input, arable crop yields are high (481 gC m^{-2} yr^{-1}; μ = 347 gC m^{-2} yr^{-1}). All other indicators were close to their aggregate mean values or disproportionally low, especially forest cover (14 %; μ = 40 %) and harvesting (0.45 m^3 ha^{-1} yr^{-1}; μ = 1.08 m^3 ha^{-1} yr^{-1}).

Areas belonging to this archetype show a clear specialisation on grasslands with intensive management regarding livestock and productivity. Other land uses are only of minor importance, especially forests.

LSA09: Low-intensity livestock farming



Archetype characterisation

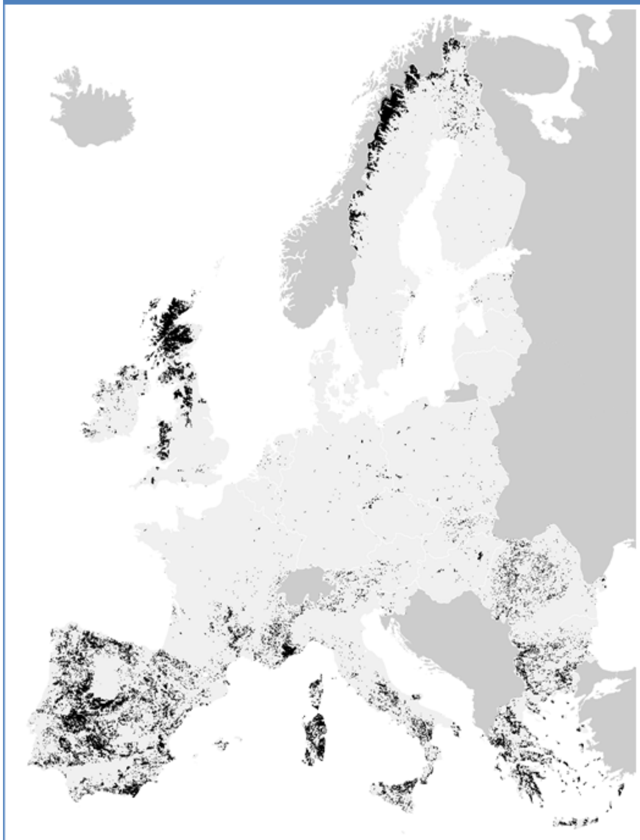


Archetype description

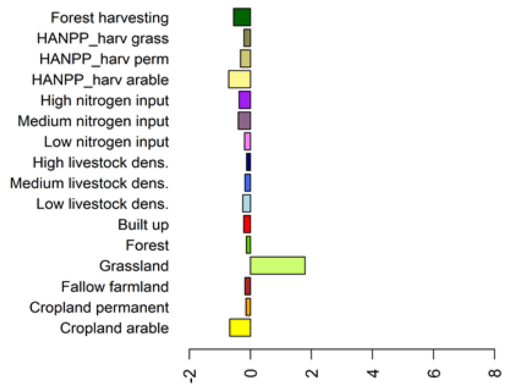
This archetype is dominated by high grassland yields (141 gC m^{-2} yr^{-1}; μ = 80 gC m^{-2} yr^{-1}) and cover (42 %; μ = 29 %) as well as low livestock density (49%; μ = 8 %). All other indicators were close to their aggregate mean values.

Areas belonging to this archetype show a specialisation on grasslands with low-intensive management regarding livestock and productivity and are likely to co-occur with other land uses without any pronounced focus.

LSA10: Low-intensity grassland area



Archetype characterisation

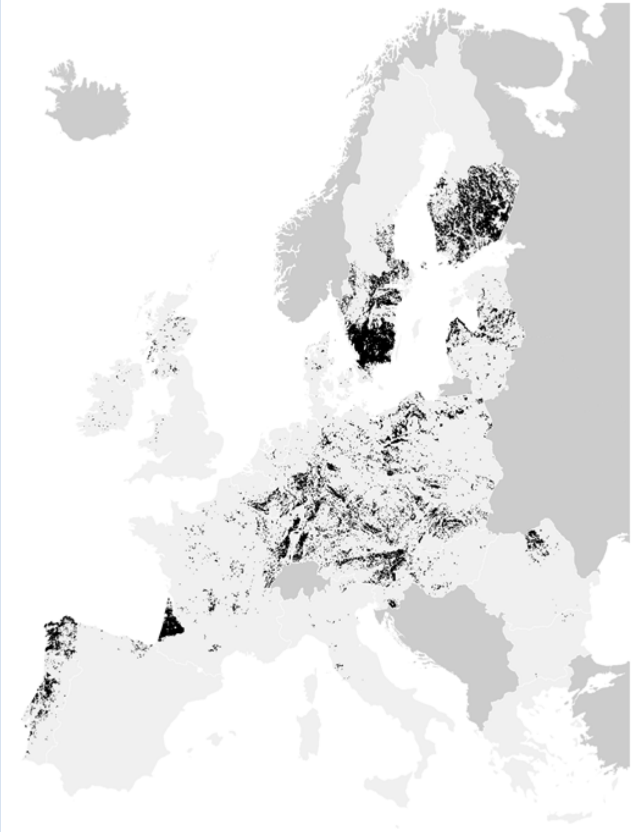


Archetype description

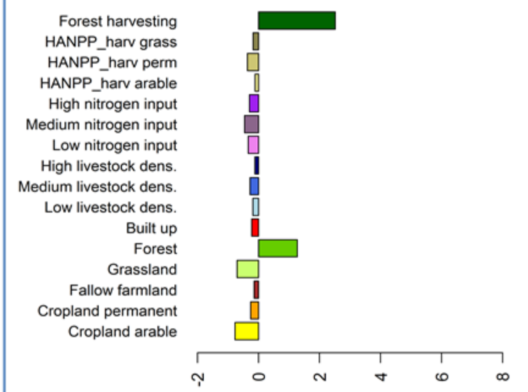
This archetype is dominated by very high grassland cover (71 %; μ = 29 %) All other indicators revealed low to very low values, especially arable cropland cover (6 % μ = 24 %), yields (152 gC m^{-2} yr^{-1}; μ = gC m^{-2} yr^{-1}), and all intensity levels of nitrogen input. Forest harvesting (0.30 m^3 ha^{-1} yr^{-1}; μ = 1.08 m3 ha^{-1} yr^{-1}), yields from grassland (62 gC m^{-2} yr^{-1}; μ = 80 gC m^{-2} yr^{-1}), and permanent crops (15 gC m^{-2} yr^{-1}; μ = 39 gC m^{-2} yr^{-1}) were also very low.

Areas belonging to this archetype are grasslands with no or very low management intensity. These grasslands are often likely to be semi-natural grasslands or scrubland under grazing and appear to be closely related to high nature conservation value farmland.

LSA11: High-intensity forest



Archetype characterisation

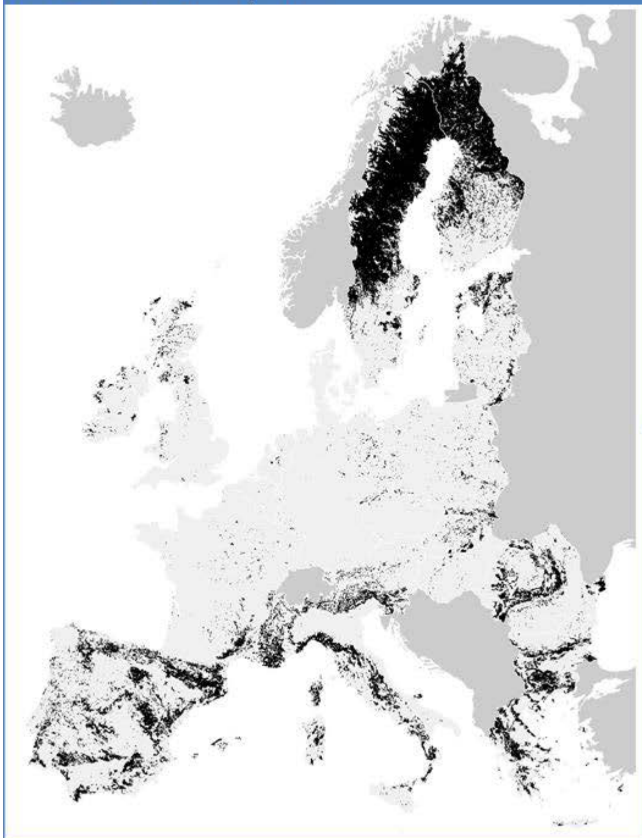


Archetype description

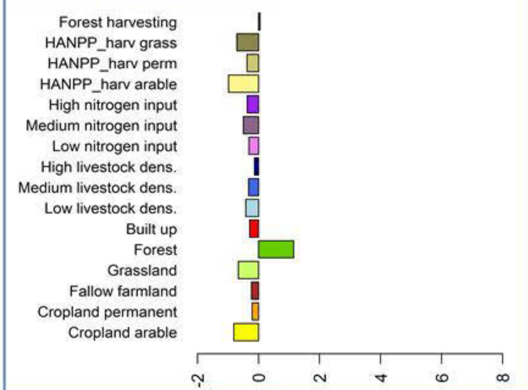
This archetype is dominated by high forest cover (82 %; μ = 40%) and harvesting (4.67 m^3 ha^{-1} yr^{-1}; μ = 1.08 m^3 ha^{-1} yr^{-1}). All other indicators were disproportionally low, especially arable cropland (4 %; μ = 24 %) and grassland cover (12 %; μ = 29 %) as well as yields from agricultural land and all intensity levels of nitrogen input and livestock density.

Areas belonging to this archetype are intensively managed forest with a clear focus on wood production.

LSA12: Low-intensity forest



Archetype characterisation

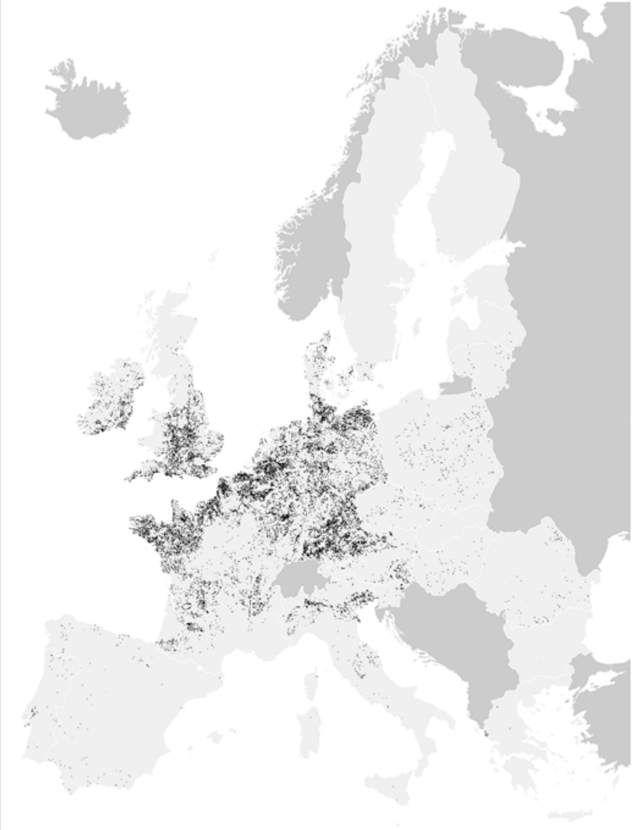


Archetype description

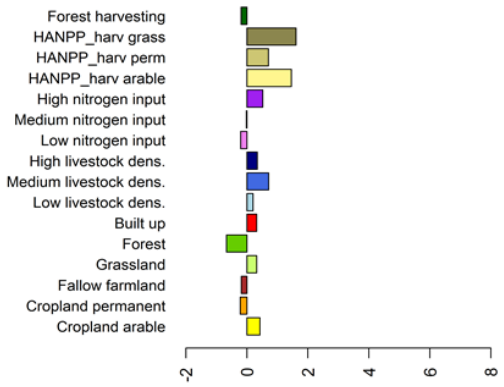
This archetype is dominated by high forest cover (78 %; μ = 40 %) and low to very low vales for all remaining indicators. Especially arable cropland (3 %; μ = 24 %) and grassland cover (13 %; μ = 29 %) revealed low values as well as yields from agricultural land (arable: 76; μ = 347, permanent: 11; μ = 39, grassland: 19; μ = 80, all values in gC m^{-2} yr^{-1}) and all intensity levels of nitrogen input and livestock density. Urban areas were disproportionally low (1 %; μ = 3 %), similar to permanent cropland (1 %; μ = 3 %) and fallow farmland (2 %; μ = 3 %). Forest harvesting was close to its aggregate mean value (μ = 1.08 m^3 ha^{-1} yr^{-1}).

Areas belonging to this archetype are (semi-)natural forests with no or low management intensity. Other land uses are only of very marginal importance.

LSA13: High-intensity agricultural mosaic



Archetype characterisation

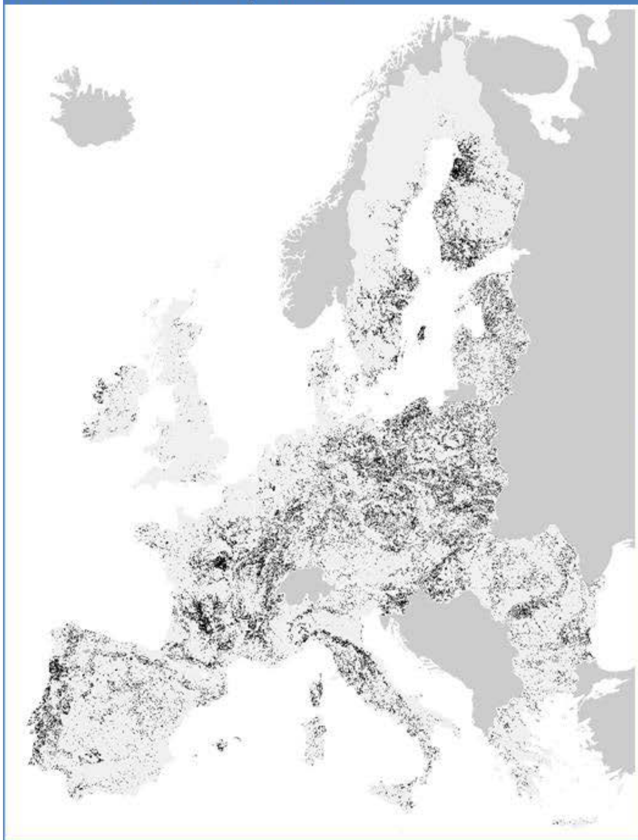


Archetype description

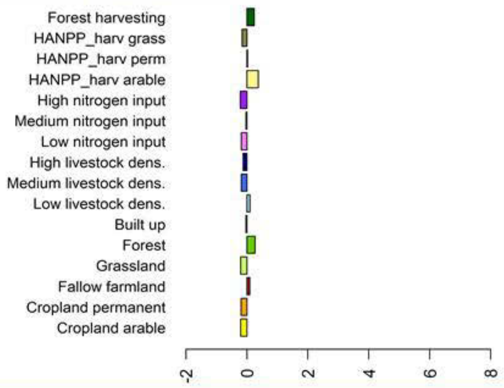
This archetype is not distinctively dominated by any land use but reveals high values of arable cropland (35 %; μ = 24 %), grassland (36 %; μ = 29 %), and built-up (5 %; μ = 3 %) cover. Permanent (1 %; μ= 3 %) and fallow farmland (2 %; μ = 3 %) but especially forest cover (19 %; μ = 40 %) were low. Management intensity was medium to high for nitrogen input (21 %; μ = 9 %) on croplands and livestock density (17 %; μ = 6 %) on grasslands. Yields on agricultural land was very high, mainly for arable cropland (749 gC m^{-2} yr^{-1}; μ = 347 gC m^{-2} yr^{-1}) and grassland (218 gC m^{-2} yr^{-1}; μ = 80 gC m^{-2} yr^{-1}), whereas forest harvesting slightly below its average (0.81 m^3 ha^{-1} yr^{-1}; μ = 1.08 m^3 ha^{-1} yr^{-1}).

Areas belonging to this archetype are mixed agricultural landscapes with low forest cover, high management intensity, and impact of settlements.

LSA14: Low-intensity mosaic



Archetype characterisation

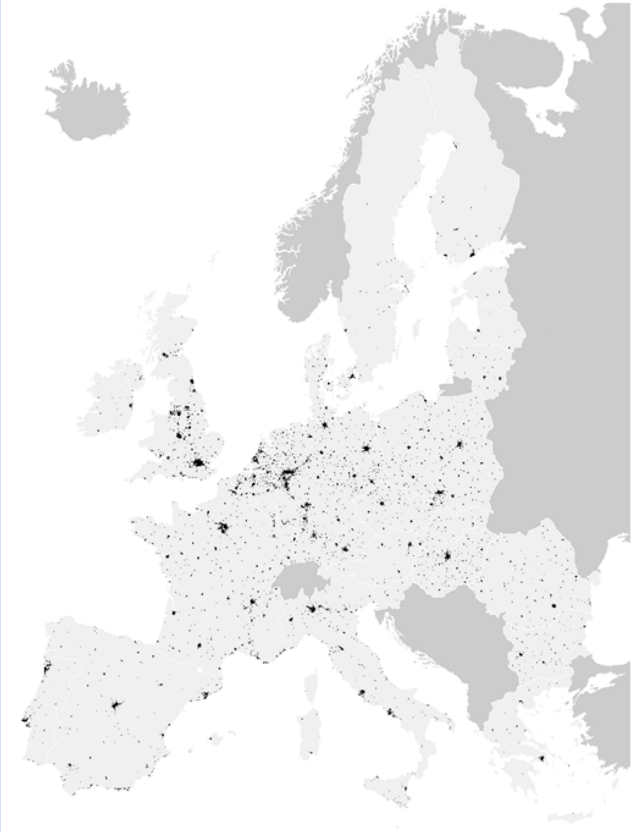


Archetype description

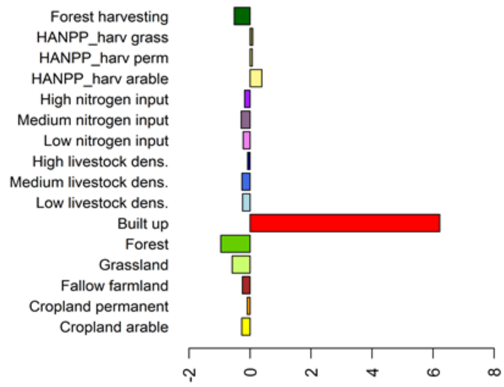
This archetype is not distinctively dominated by any land use and almost all indicators reveal values close to or slightly below their aggregate mean. Exceptions were forest cover (49 %; μ = 40 %) and harvesting (1.42 m^3 ha^{-1} yr^{-1}; μ = 1.08 m^3 ha^{-1} yr^{-1}) as well as yields from arable cropland (450 gC m^{-2} yr^{-1}; μ = 347 gC m^{-2} yr^{-1}).

Areas belonging to this archetype are mixed landscapes with various land uses with a slight predominance of forest systems. When land is used for agriculture or forestry, management intensity is low.

LSA15: Urban built-up



Archetype characterisation



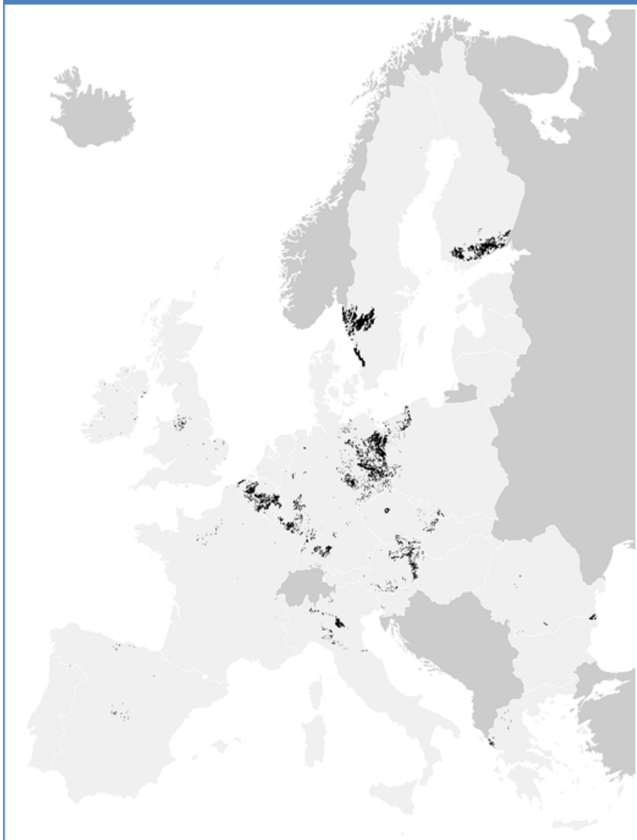
Archetype description

This archetype is dominated by high urban built-up cover (39 %; μ = 3 %) and low values for all other land uses. Especially forest (9 %; μ = 40 %) and grassland (15 %; μ = 29 %) cover were disproportionally low. Arable croplands revealed low extents (17 %; μ = 24 %), but high yields (453 gC m^{-2} yr^{-1}; μ = 347 gC m^{-2} yr^{-1}) while nitrogen input was low for all intensity levels. On grasslands, yields were close to their aggregate mean value (μ = 80 gC m^{-2} yr^{-1}) and livestock density was low for all intensity levels.

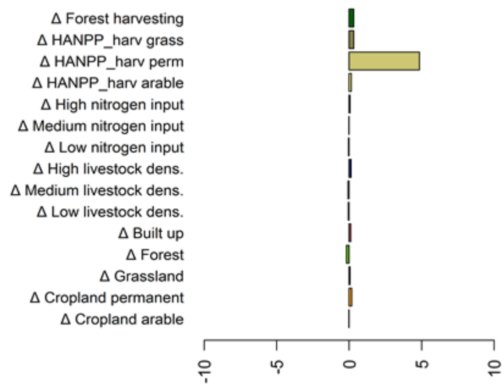
Areas belonging to this archetype are substantially influenced by anthropogenic use with hardly any (semi-)natural land cover. Existing croplands may represent peri-urban regions where crops are cultivated.

Figure SI V-8: Detailed descriptions of ACT01 to ACT17.

ACT01: Increasing yields in permanent crops



Archetype characterisation

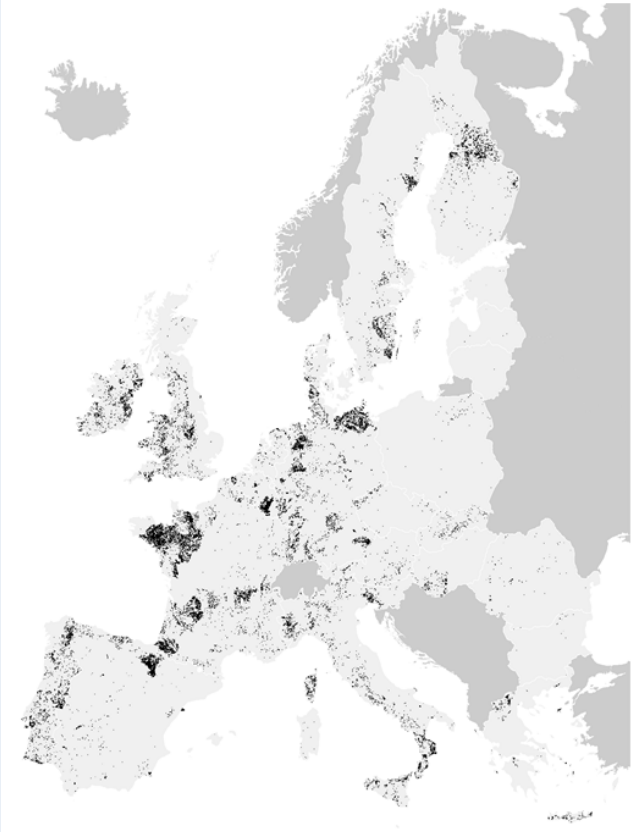


Archetype description

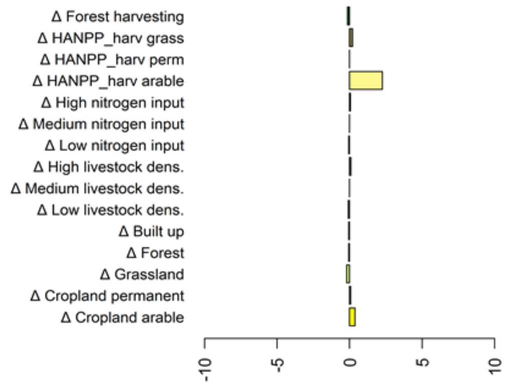
This archetype is dominated by high increases in permanent crop yields (+276 gC m^{-2} yr^{-1}; μ = +9 gC m^{-2} yr^{-1}). Yields from arable cropland (+38 gC m^{-2} yr^{-1}; μ = +18 gC m^{-2} yr^{-1}) and grassland (+9 gC m^{-2} yr^{-1}; μ = -6 gC m^{-2} yr^{-1}) as well as forest harvesting (+0.42 m^3 ha^{-1} yr^{-1}; μ = +0.23 m^3 ha^{-1} yr^{-1}) revealed slight increases. All other indicators remained more or less stable.

Areas belonging to this archetype showed an intensification of land use in terms of productivity, especially for croplands with permanent crops.

ACT02: Increasing cropland yields



Archetype characterisation

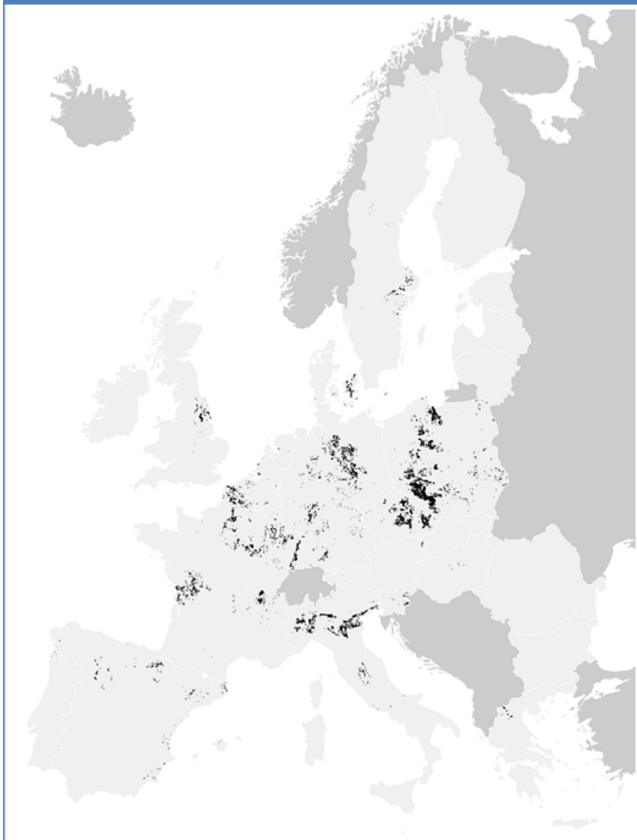


Archetype description

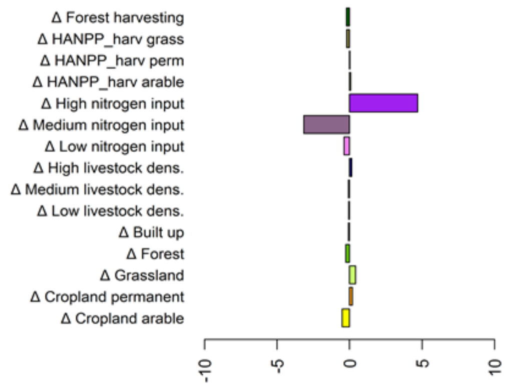
This archetype is dominated by high increases in arable cropland yields (+311 gC m^{-2} yr^{-1}; μ = +18 gC m^{-2} yr^{-1}) and an above average trend in arable cropland cover (-0.81 %; μ = -3.05 %), i.e. a weaker decline of arable cropland cover compared to the aggregate mean value. Grassland cover (-0.33 %; μ = +1.60 %) slightly decreased with marginally increasing grassland yields (+3.5 gC m^{-2} yr^{-1}; μ = -6.2 gC m^{-2} yr^{-1}). All other indicators remained more or less stable.

Areas belonging to this archetype showed an intensification of land use in terms of productivity, especially for croplands with permanent crops. Arable cropland decline was less pronounced compared to the aggregate mean.

ACT03: Intensification towards high-intensity cropland



Archetype characterisation

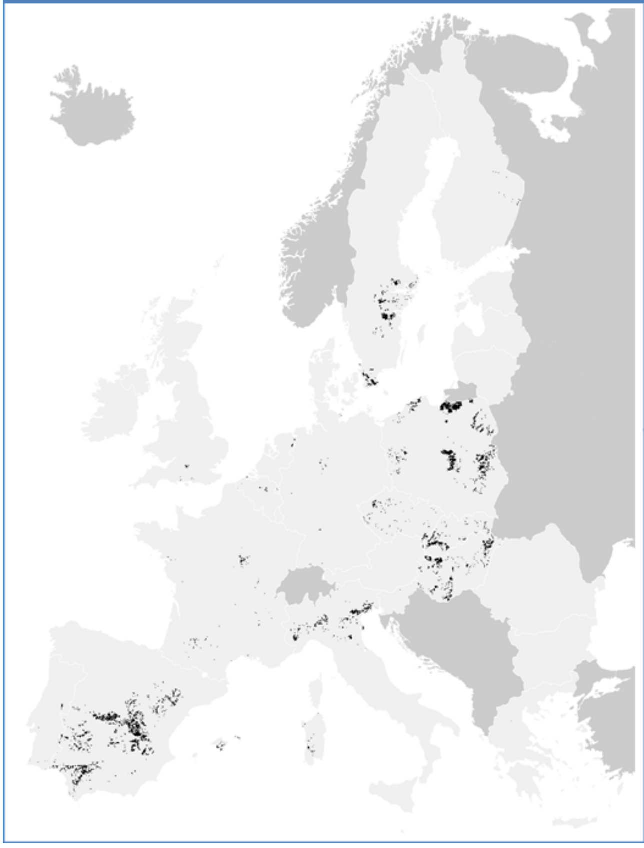


Archetype description

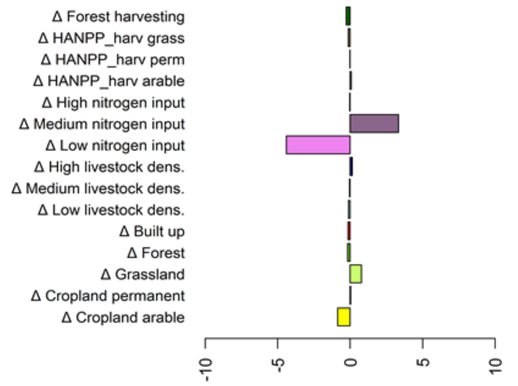
This archetype is dominated by a shift from medium (-55.46 %; μ = -0.78 %) to high nitrogen input (+59.73 %; μ = -0.03 %) on arable croplands that revealed a decreasing trend (-6.07 %; μ = -3.05 %). Grassland cover slightly increased (+5.56 %; μ = +1.60 %) while forest cover was increasing slightly below the aggregate average (μ = +1.67 %). All other indicators remained more or less stable.

Areas belonging to this archetype showed a high level intensification of arable cropland with increasing input intensity on decreasing area that was likely changed to grasslands. This trend could be characterised as land-use specialisation or polarisation.

ACT04: Intensification towards medium-intensity cropland



Archetype characterisation

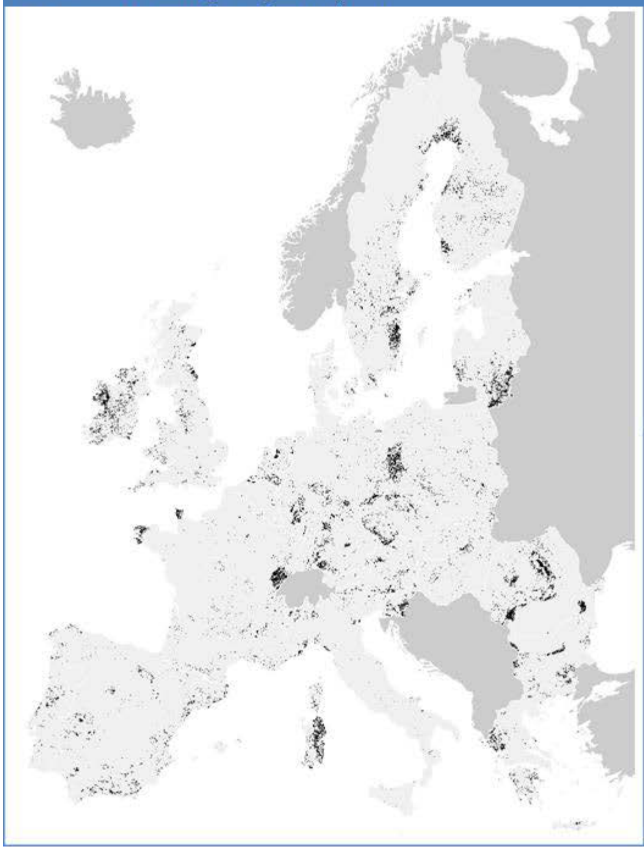


Archetype description

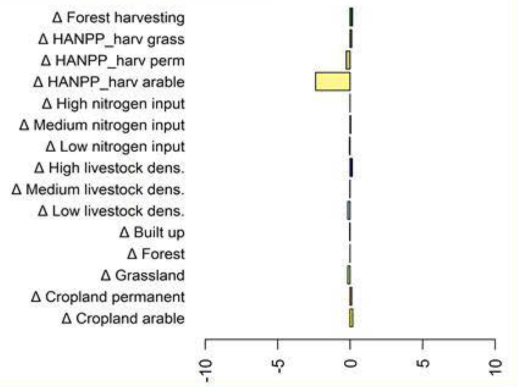
This archetype is dominated by a shift from low (-56.66 %; μ = +0.80 %) to medium nitrogen input (+57.16 %; μ = -0.78 %) on arable croplands that revealed a decreasing trend (-8.16 %; μ = -3.05 %). Grassland cover increased (+8.88 %; μ = +1.60 %). All other indicators remained more or less stable.

Areas belonging to this archetype showed a low level intensification of arable cropland with increasing input intensity on decreasing area that was likely changed to grasslands. This trend could be characterised as land-use specialisation or polarisation.

ACT05: Declining cropland yields



Archetype characterisation

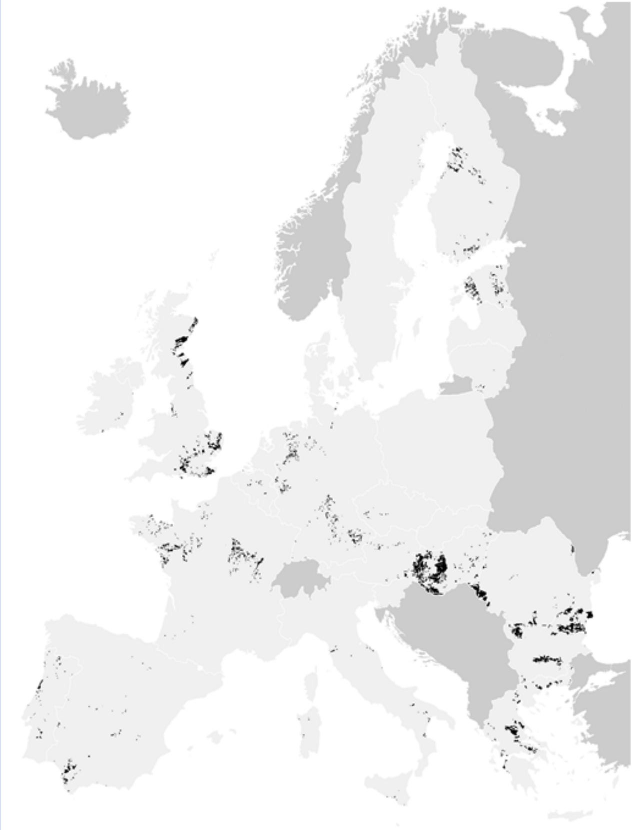


Archetype description

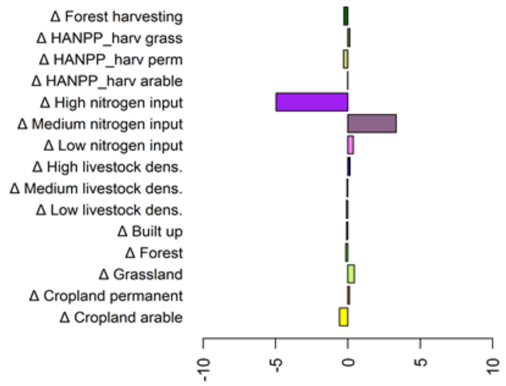
This archetype is dominated by strong decreases in arable cropland yields (-290.27 gC m^{-2} yr^{-1}; μ = +18.14 gC m^{-2} yr^{-1}). Yields from permanent crops decreased slightly (-5.84 gC m^{-2} yr^{-1}; μ = +8.83 gC m^{-2} yr^{-1}) while all other indicators remained more or less stable.

Areas belonging to this archetype showed a de-intensification of especially arable croplands regarding productivity in a more or less stable land configuration.

ACT06: De-intensification of high-intensity cropland



Archetype characterisation

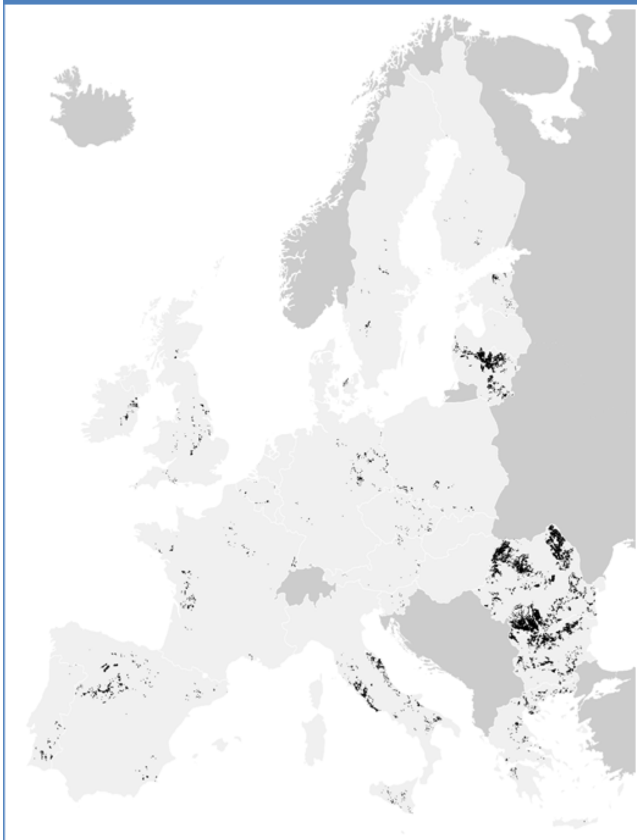


Archetype description

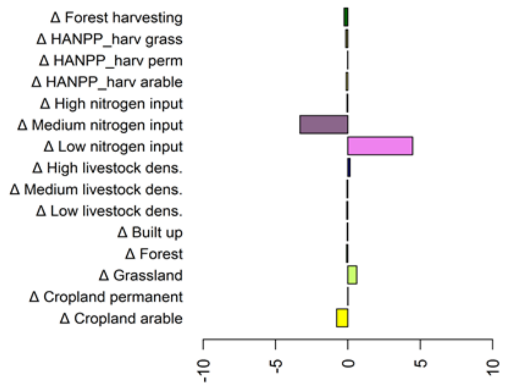
This archetype is dominated by a shift from high (-63.05 %; μ = -0.03 %) to medium nitrogen input (+57.26 %; μ = -0.78 %) on arable croplands that revealed a decreasing trend (-6.49 %; μ = -3.05 %). Grassland cover increased (+5.83 %; μ = +1.60 %) while yields from permanent crops (-7.51 gC m^{-2} yr^{-1}; μ = +8.83 gC m^{-2} yr^{-1}) slightly decreased. All other indicators remained more or less stable.

Areas belonging to this archetype showed a high level de-intensification of arable cropland with decreasing input intensity on decreasing area that was likely changed to grasslands.

ACT07: De-intensification of medium-intensity cropland



Archetype characterisation

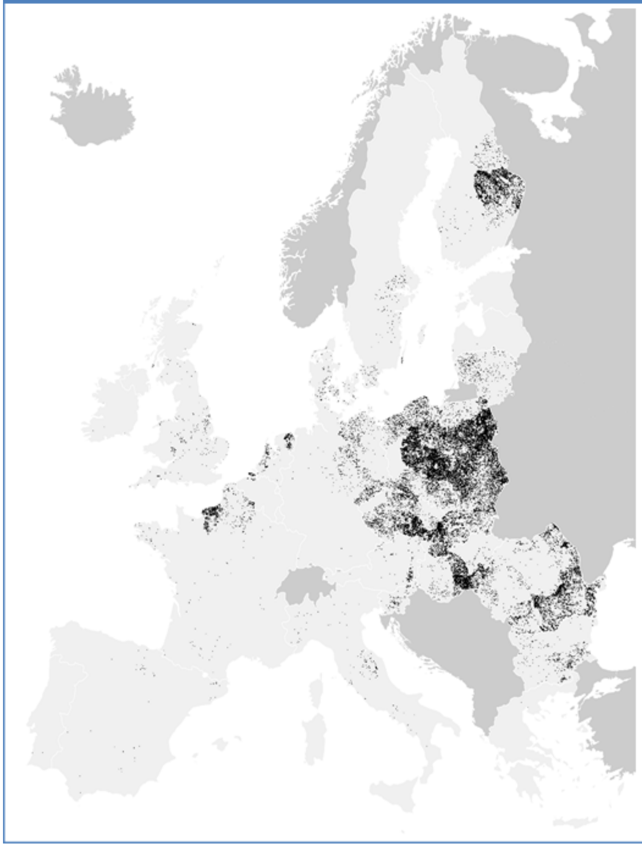


Archetype description

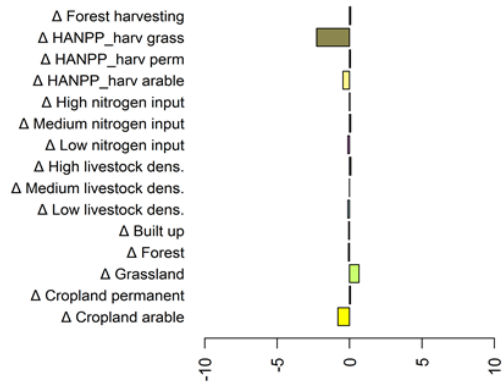
This archetype is dominated by a shift from medium (-58.12 %; μ = -0.78 %) to low nitrogen input (+59.34 %; μ = +0.80 %) on arable croplands that revealed a decreasing trend (-7.64 %; μ = -3.05 %). Grassland cover increased (+7.33 %; μ = +1.60 %). All other indicators remained more or less stable.

Areas belonging to this archetype showed a low level de-intensification of arable cropland with decreasing input intensity on decreasing area that was likely changed to grasslands.

ACT08: Declining grassland yields



Archetype characterisation

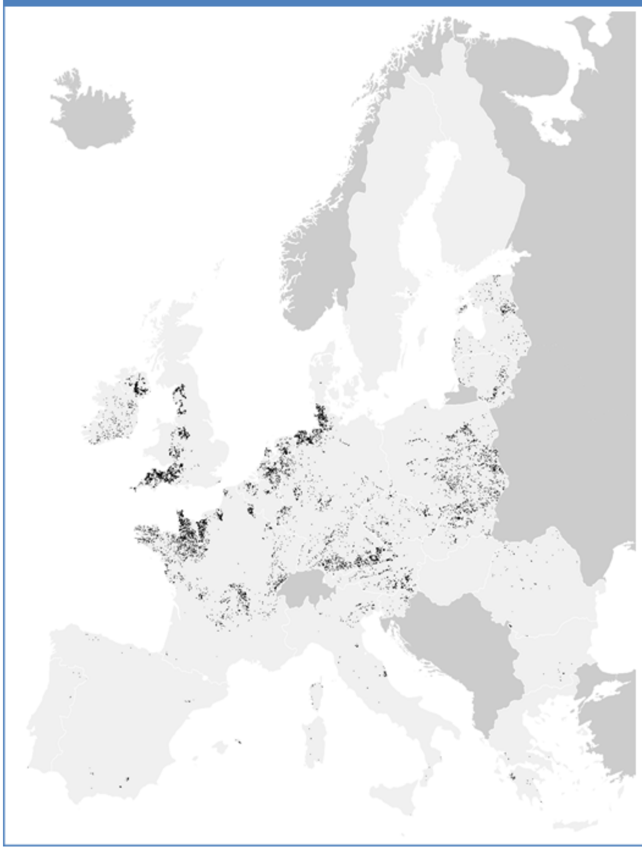


Archetype description

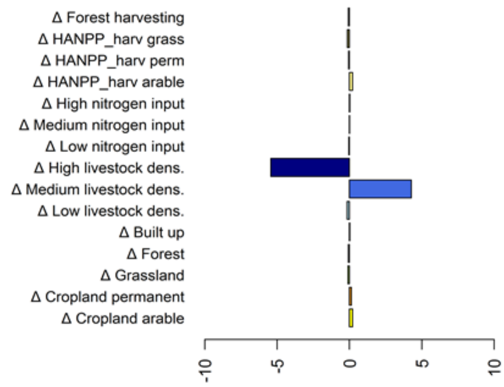
This archetype is dominated by a strong decrease in grassland yields (-111.33 gC m^{-2} yr^{-1}; μ = -6.21 gC m^{-2} yr^{-1}) as well as decreases in arable cropland cover (-7.79 %; μ = -3.05 %) and yields (-40.64 gC m^{-2} yr^{-1}; μ = +18.14 gC m^{-2} yr^{-1}). Grassland cover revealed an increasing trend (+7.73 %; μ = +1.60 %). All other indicators remained more or less stable.

Areas belonging to this archetype showed a de-intensification of grasslands manifested by area expansion and yield decreases that went along with declining productivity and area contraction on arable croplands.

ACT09: De-intensification of high-intensity livestock farming



Archetype characterisation

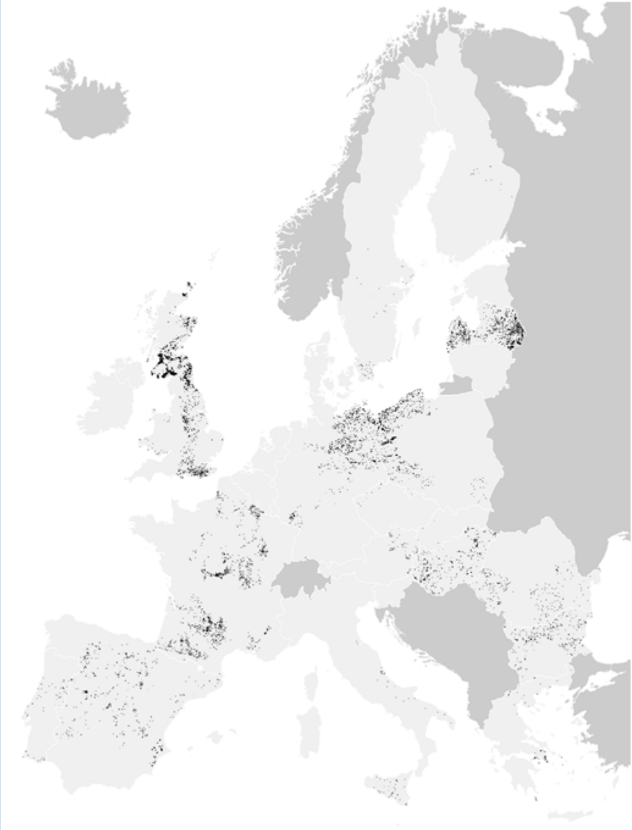


Archetype description

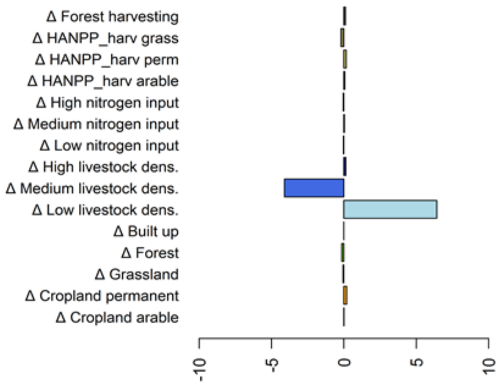
This archetype is dominated by a shift from high (-34.62 %; μ = -1.10 %) to medium livestock density (+34.77 %; μ = + 0.25 %). Arable croplands decreased less pronounced compared to the aggregate trend (-1.73 %; μ = -3.05 %) and revealed an increase in yields (+47.47 gC m^{-2} yr^{-1}; μ = +18.14 gC m^{-2} yr^{-1}). All other indicators remained more or less stable.

Areas belonging to this archetype showed a high level de-intensification of grasslands with decreasing management intensity regarding livestock density embedded in a more or less stable land configuration. A slight intensification of arable croplands with increasing yields on decreasing area was observable.

ACT10: De-intensification of medium-intensity livestock farming



Archetype characterisation

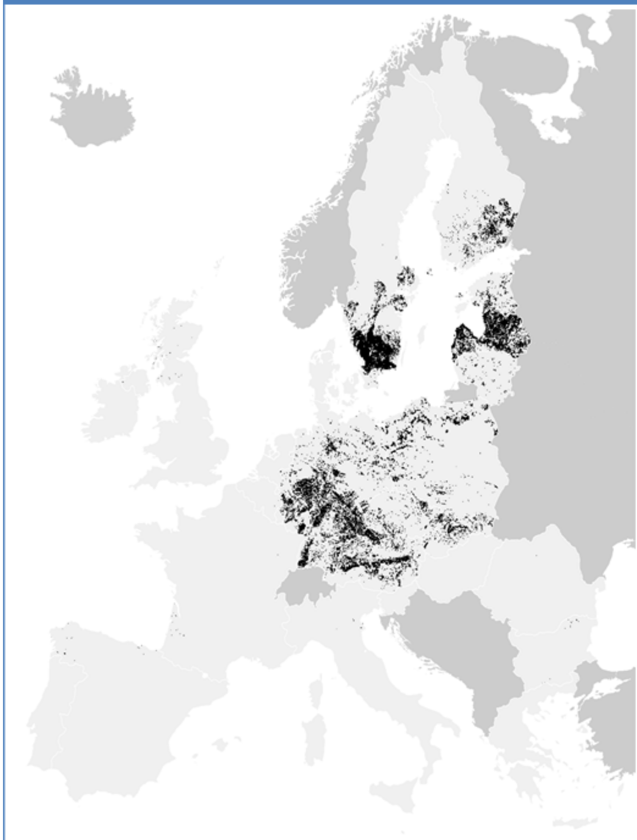


Archetype description

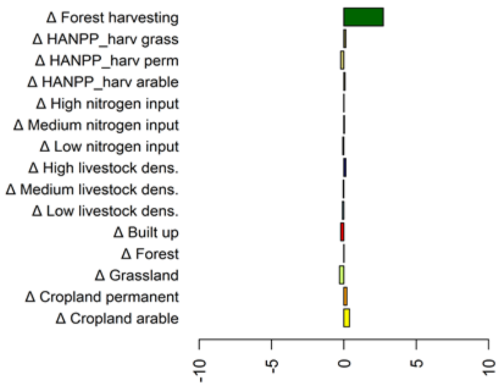
This archetype is dominated by a shift from medium (-32.83 %; μ = +0.25 %) to low livestock density (+33.22 %; μ = +0.86 %). All other indicators remained more or less stable.

Areas belonging to this archetype showed a low level de-intensification of grasslands with decreasing management intensity regarding livestock density embedded in a more or less stable land configuration.

ACT11: Forestry intensification



Archetype characterisation

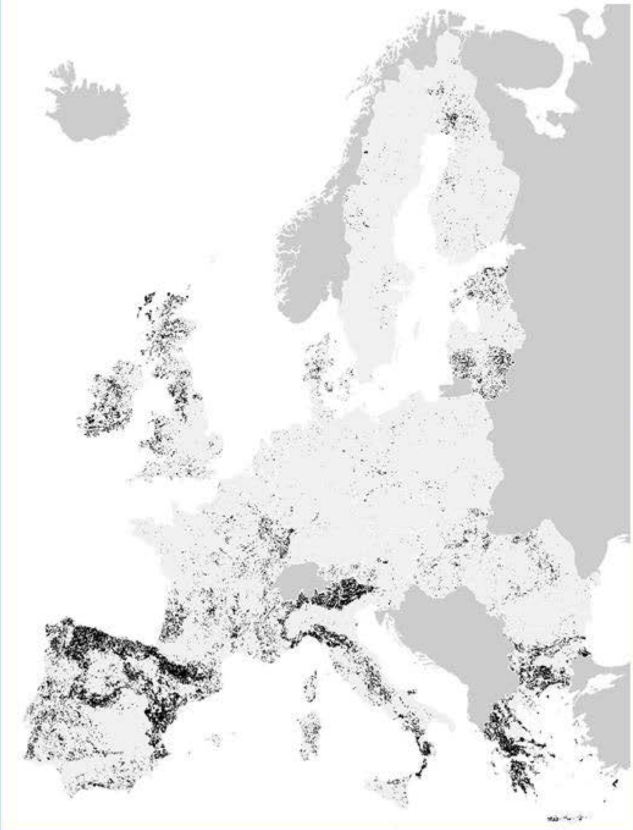


Archetype description

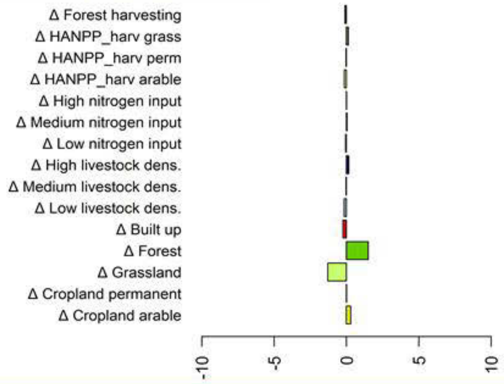
This archetype is dominated by a strong increase in forest harvesting (+1.82 $m^3\ ha^{-1}\ yr^{-1}$; μ = +0.23 $m^3\ ha^{-1}\ yr^{-1}$) and a stable permanent cropland cover (μ = -0.38 %) as well as a less pronounced arable cropland decrease compared to its aggregate trend (-0.78 %; μ = -3.05 %). Grassland cover decreased slightly (-1.25 %; μ = +1.60 %) whereas urban built-up increased less pronounced compared to its aggregate trend (+0.09 %; μ = +0.34 %). Yields from permanent crops decreased slightly (-3.20 gC $m^{-2}\ yr^{-1}$; μ = +8.83 gC $m^{-2}\ yr^{-1}$). All other indicators remained more or less stable.

Areas belonging to this archetype showed an intensification of wood production.

ACT12: Forest expansion over grassland



Archetype characterisation

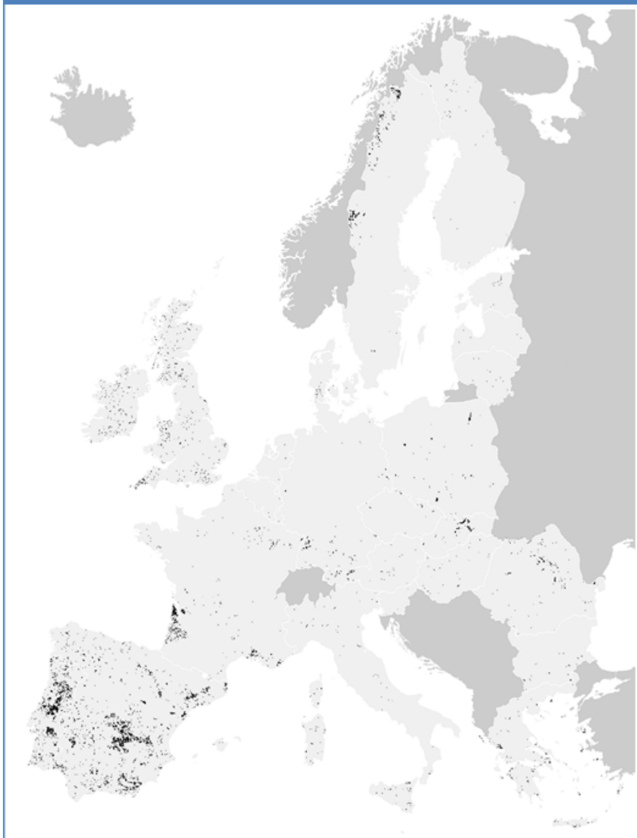


Archetype description

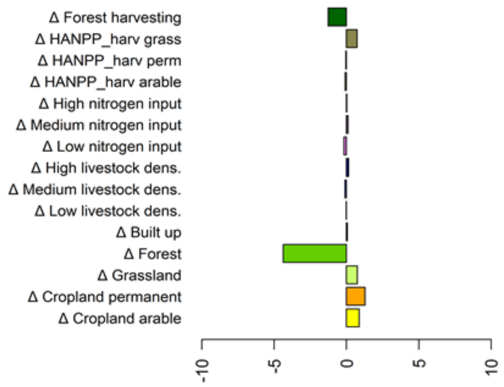
This archetype is dominated by a strong increase in forest cover (+10.80 %; μ = +1.67 %) and a strong decrease in grassland cover (-10.52 %; μ = +1.60 %). Arable cropland cover revealed a less pronounced decrease compared to its aggregate trend (-1.32 %; μ = -3.05 %). All other indicators remained more or less stable.

Areas belonging to this archetype showed a conversion from grassland to forest-dominated landscapes with less declining arable cropland areas compared to the Europe-wise trend.

ACT13: Deforestation for agricultural expansion



Archetype characterisation

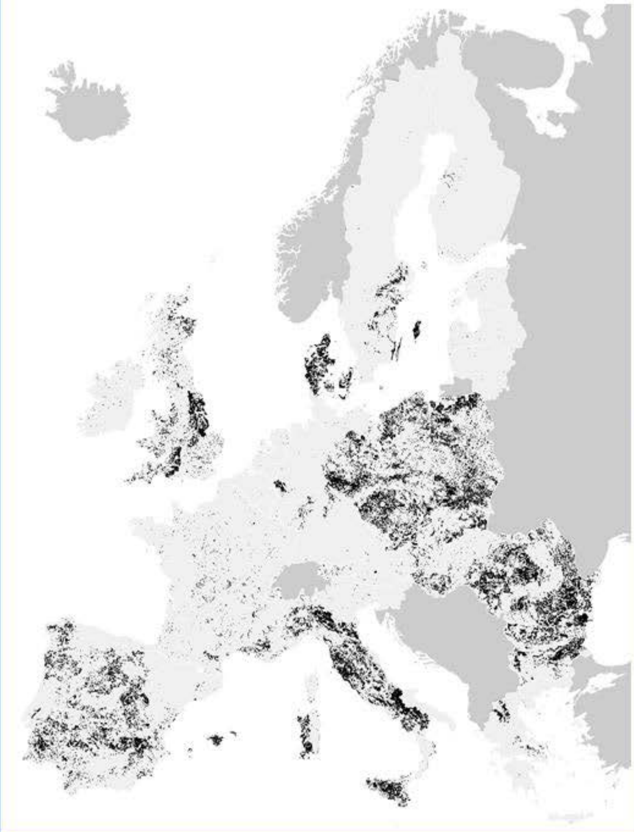


Archetype description

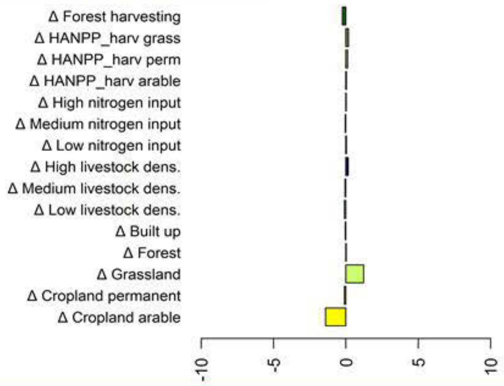
This archetype is dominated by a strong decrease in forest cover (-24.74 %; μ = +1.67 %) and revealed substantial increases in arable cropland (+2.17%; μ = -3.05 %), permanent cropland (+1.96 %; μ = -0.38 %), and grassland (+8.68 %; μ = +1.60 %) cover. Yields from grasslands revealed an increasing trend (+27.95 gC m^{-2} yr^{-1}; μ = -6.21 gC m^{-2} yr^{-1}) while forest harvesting was decreasing (-0.49 m^3 ha^{-1} yr^{-1}; μ = +0.23 m^3 ha^{-1} yr^{-1}). All other indicators remained more or less stable.

Areas belonging to this archetype showed a substantial forest cover and productivity decline while agricultural areas revealed a marked expansion along with increasing yields on grasslands.

ACT14: Cropland-grassland conversions



Archetype characterisation

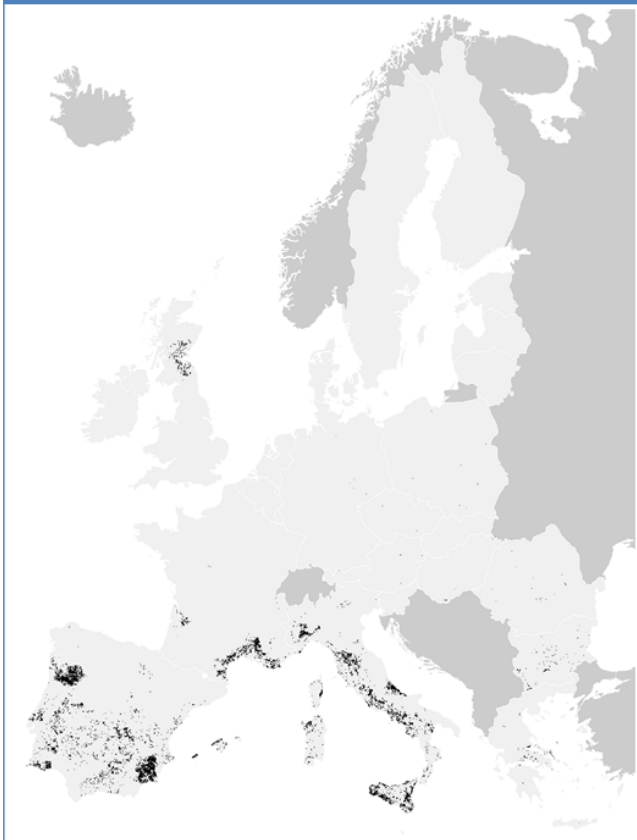


Archetype description

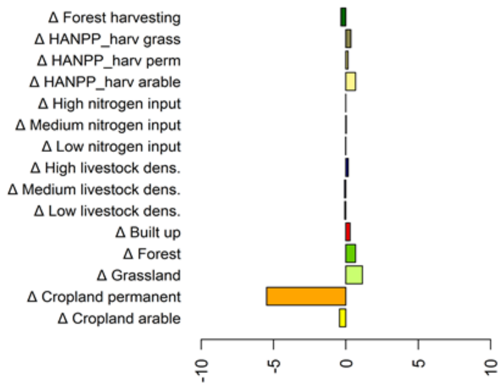
This archetype is dominated by a strong decrease in arable cropland cover (-11.43 %; μ = -3.05 %) and a substantial increase in grassland cover (+13.11 %; μ = +1.60 %). All other indicators remained more or less stable.

Areas belonging to this archetype showed a conversion from arable cropland to grassland-dominated landscapes embedded in a more or less stable land configuration.

ACT15: Permanent cropland loss



Archetype characterisation

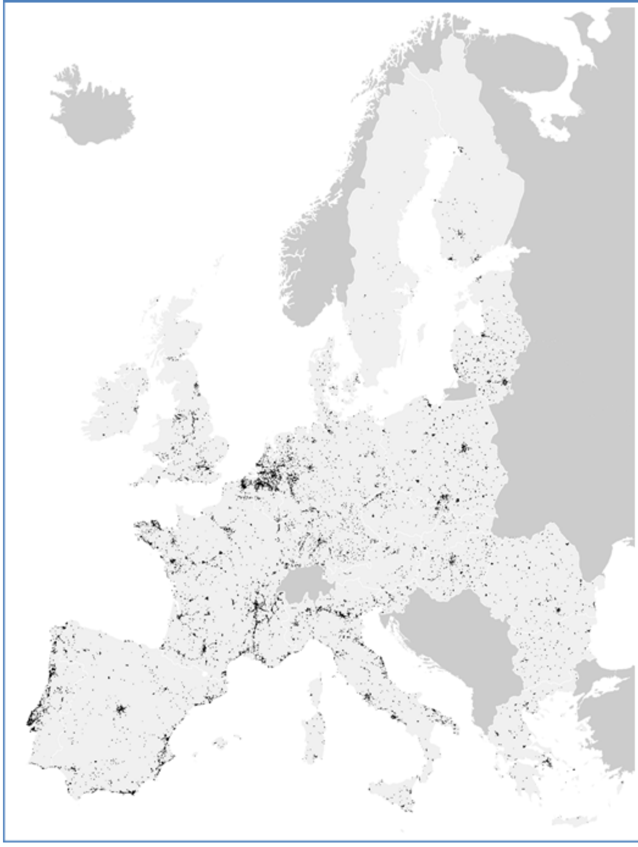


Archetype description

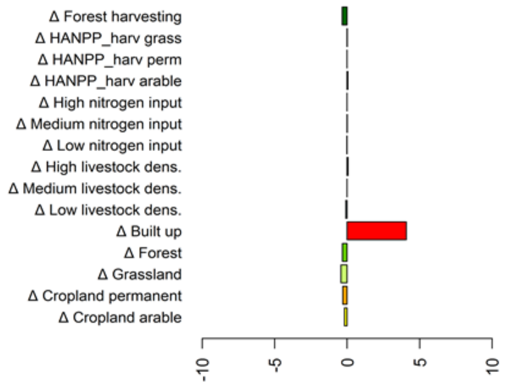
This archetype is dominated by a decrease in cropland cover, especially pronounced for permanent crops (-10.42%; μ = -0.38 %). Grassland (+12.39 %; μ = +1.60 %), forest (+5.74 %; μ = +1.67 %), and built-up cover (0.68 %; μ = +0.34 %) revealed increasing trends. Arable cropland declined markedly (-5.68 %; μ = -3.05 %) while yields from arable croplands increase (105.25 gC m^{-2} yr^{-1}; μ = +18.14 gC m^{-2} yr^{-1}). All other indicators remained more or less stable.

Areas belonging to this archetype showed a general decline of cropland areas, particularly pronounced for permanent crops, while their yields revealed increasing trends. Along with substantial increases in forest and grassland cover, this could indicate a land-use specialisation or polarisation.

ACT16: Urban expansion



Archetype characterisation

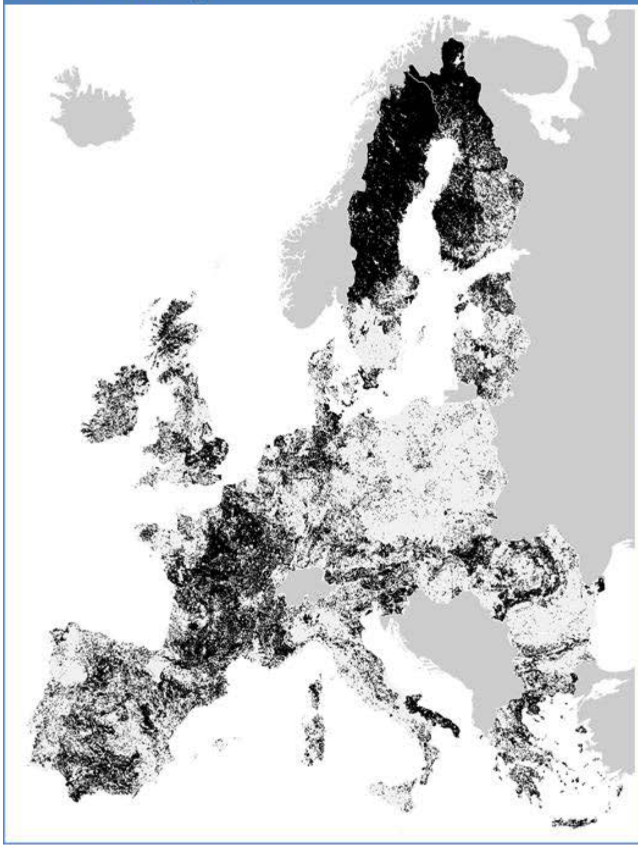


Archetype description

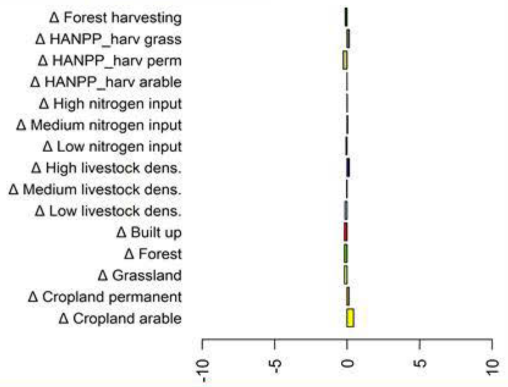
This archetype is dominated by a strong increase of urban built-up cover (+5.20 %; μ = +0.34 %). All other land use classes showed decreasing trends (forest: -0.28 %; μ = +1.67 %, grassland: -2.36 %; μ = +1.60 %, permanent cropland: -0.93 %; μ = -0.38 %, arable cropland: -4.13 %; μ = -3.05 %). Forest harvesting revealed hardly any change and was thus below the aggregate trend of slightly increasing forest harvesting (μ = +0.23 m^3 ha^{-1} yr^{-1}). All other indicators remained more or less stable.

Areas belonging to this archetype showed a substantial expansion of urban built-up cover at the expense of vegetated land cover thus strengthening the anthropogenic impact on (semi-)natural landscapes.

ACT17: Stability



Archetype characterisation



Archetype description

This archetype was not dominated by any change in land cover or land use intensity. All indicators exhibited no or only minor changes over the study period. The strongest changes were the, compared to its aggregate trend, less pronounced decline in arable cropland cover (-0.41 %; μ = -3.05 %) and slight decreases in grassland cover (-0.20 %; μ = +1.60 %). Forest (+0.53 %; μ = +1.67 %) and urban built-up (+0.11 %; μ = +0.34 %) cover revealed less pronounced increases compared to their aggregate trends.

Areas belonging to this archetype showed only marginal changes over the study period and can thus be characterised as areas of stability regarding area extent and management intensity.

Text SI V-1: Detailed description of the additive closed budget approach to generate indicators on the extent of broad land-use classes.

To derive indicators on the extent of broad land-use classes, we largely relied on the CORINE land-cover database that does not provide land-cover information for Sweden and Finland (1990) and Greece (2006). We resolved this issue by using land-cover data of the year 2000 for these countries. To ensure temporal dynamics, we reconciled this data with NUTS2 census statistics on the extent of land-use types and on biomass flows (i.e., land-use intensity) for the respective target years. To estimate class fractions per grid cell for 1990 and 2006, shares for each CORINE land-cover class were calculated from CORINE land-cover maps with 100 m^2 resolution and applied to the respective years.

First, the share of all non-forest and non-farmland (i.e., cropland and pasture) areas for each 1 km^2 pixel was calculated by excluding built-up area, unproductive and wetland areas, and wilderness areas. Therefore, a built-up and infrastructure layer from the year 2000 was used, which contains information on the percentage of sealed area per grid cell (Kopecky and Kahabka 2009). Unlike categorical CORINE land-cover data, this layer allowed the assessment of sparsely distributed built-up and infrastructural areas (e.g., roads or farm buildings), especially in rural regions. The spatial extent of unproductive areas and wetlands were taken directly from CORINE, whereas the wilderness layer was derived from a wilderness quality index map (EEA 2012) since the CORINE database does not contain explicit information on wilderness areas.

Second, cropland area demand was estimated using cropland statistics from the CAPRI (Common Agricultural Policy Regionalised Impact Modelling System) database for the years 1990 and 2006. These data were provided on NUTS2 level and aggregated to 12 major crop types (cereals except rice, flax & hemp, fodder, fruits, oilseeds except olives, olives, pulses, rice, roots & tubers, sugar beet, vegetables and other crops, as well as wine and grapes) plus fallow cropland as an additional type. Cropland area demand was spatially allocated by using the patterns of the corresponding 13 CAPRI-DynaSpat layers (reference year 2006) and clipped by the extent of CORINE-based arable land-cover classes for the respective year (except pastures, see below).

Third, forest area demand was estimated using national statistics from the State of European Forests (SoEF) database (Forest Europe et al. 2011) that were allocated to regional-scale administrative units (NUTS3 to NUTS1) using weights based on regional statistics for the year 2000. Three datasets were then used to allocate forest area values to the grid level: (i) pattern and extent of the CORINE forest classes, (ii) data on other wooded land for the year 2010 (Forest Europe et al. 2011) and (iii) the Forest Map of Europe (Gunia et al. 2011).

Fourth, the remaining land was used to allocate grazing areas for which statistics were taken from the CAPRI database. Pastures and meadows were defined as core areas for grazing and the spatial extent and patterns of the corresponding CORINE land-cover class were used as weights to allocate grazing areas. The resulting raster map represents the spatial coverage of the six land use/cover classes as fractions [%] per 1 km^2 pixel (Plutzar et al. 2015).

Text SI V-2: Detailed description of the generation of land-use intensity indicators.

To estimate forest harvesting intensity, we used data on sub-national forest harvesting volumes [m^3] and forest area [ha] derived from national forestry reports, statistical yearbooks and databases, and by contacting national experts (see Levers et al. 2014). The datasets were harmonised to correct for differences in national harvesting definitions, and gaps were filled by using national harvesting statistics from the closest year to the gap for which data were available. To estimate forest harvesting rates at the pixel scale, we used a linear regression to explain observed patterns of forest harvesting rates with a set of spatial determinants (Verkerk et al. 2015) and applied the resulting equation to predict forest harvesting rates for each pixel. This prediction map served, after normalisation, as a suitability map for allocating harvested volumes. The final map was validated by comparing predicted forest harvesting rates to observed data in regions where data was available as either high resolution plot data or higher resolution sub-national data as used in the analysis (Verkerk et al. 2015).

To estimate the input intensity of croplands, we relied on the data produced by Temme and Verburg (2011) who used data from the Land Use/Cover Area Frame Statistical Survey (LUCAS) and the Common Agricultural Policy Regionalised Impact Modelling System (CAPRI), which includes Farm Structure Survey (FSS) data, to calculate crop-specific nitrogen application rates which were subsequently stratified into three intensity classes: (i) low intensity with < 50 kg N/ha, (ii) medium intensity with 50-150 kg N/ha, and (iii) high intensity with > 150 kg N/ha. These data sets were then used to predict the nitrogen application for all locations classified as arable land (based on the CORINE 2000 classification) by using a multinomial logistic regression with a set of environmental and socio-economic covariates.

We cut off HANPP harvesting intensity values at 1000 gC m^{-2} yr^{-1} since (relatively) large amounts of biomass harvested can occur on (relatively) small areas. This fact can lead to a small number problem when calculating change ratios between years since even small area in/decreases would relate to substantial changes in the intensity value. Hence, we used an ecologically acceptable threshold (1000 gC m^{-2} yr^{-1} correspond to 20 tons of harvested dry matter) to conservatively calculate harvesting intensity levels and especially changes therein since pixels exceeding the threshold were set to the highest intensity level.

Text SI V-3: Expert workshop on evaluating Land-System Archetypes and Archetypical Change Trajectories.

We interpreted and discussed the resulting archetypes (LSAs and ACTs) in a 3-day expert workshop in October 2014 (Workshop participants: Karlheinz Erb, Stephan Estel, Martin Rudbeck Jepsen, Tobias Kuemmerle, Christian Levers, Marc Metzger, Patrick Meyfroidt, Daniel Müller, Jonas Østergaard Nielsen, Tobias Plieninger, Anette Reenberg, Julia Stürck, and Peter H. Verburg). The overall goal of the workshop was to obtain a good understanding of how well the archetypes capture complex interactions of land-use change and their determinants and drivers in the EU. This was achieved by assessing, labelling, and qualitatively validating the identified archetypes.

During the workshop, facilitators briefly presented the aims of the workshop and introduced the final clustering results to the participants. After an initial feedback round, all SOM clusters were visualised on a big screen and discussed with respect to their thematic value, spatial distribution, and the relative importance and values of the contributing variables. On a second screen, we simultaneously visualised flower plots, bar plots, and cluster summaries to assist the interpretation. We also developed short narratives describing each archetype. In a second step, we zoomed into specific regions to discuss regional characteristics of each archetype.

An important aspect of the expert evaluation was also to decide upon the most plausible number of clusters, which may differ from the statistically optimal number of clusters. Accordingly, we discussed whether archetypes were too small to stand alone, whether two or more archetypes were characterised by similar patterns/changes and should therefore be joined together, or whether archetypes were too heterogeneous in terms of their patterns and indicator values and should be split up (i.e., a clustering with a higher numbering of clusters should be chosen as a starting point). We decided on expanding the number of clusters for the LSA assessment in comparison to the “optimal” value selected by the DB index (12 clusters) to 16 to split up the category of forestry systems into a low-intensity and a high-intensity archetype.

Text SI V-4: Description of spatial patterns of Land-System Archetypes.

Land systems dominated by high-intensity croplands (pertaining to arable and permanent croplands) occur in particularly in the Po valley (Italy), in the eastern parts of Austria and the Czech Republic, and parts of Belgium, Germany, and Sweden. Large-scale permanent croplands predominantly occur in the Mediterranean region, especially pronounced on the eastern coast of Spain, the southern parts of Spain, Italy, and France as well as on Cyprus and in parts of Greece. High-intensity arable croplands (pertaining to yields and fertiliser input) largely occur in central Europe, particularly in Denmark, the Po valley (Italy), northern France, eastern England, throughout Germany, and in parts of Poland and the Czech Republic. Medium-intensity arable croplands are mainly located in northern Spain, western France, throughout Poland, and particularly pronounced in the border region between Romania and Bulgaria as well as in Hungary and Slovakia. Low-intensity arable croplands are dominant in eastern Europe, particularly in Lithuania, the eastern foothills of the Carpathians in Romania, and in parts of Poland, Bulgaria, Italy, and Spain. Fallow farmland predominantly occurs in the Baltic countries, eastern Poland, central Romania and in the mountainous regions in Austria, France, and Italy (Alps) and France and Spain (Pyrenees).

Land systems dominated by high-intensity livestock farming (pertaining to yields and livestock density) occur in the Netherlands, the Alp region in Germany, the Normandy in France, and on Ireland. Medium-intensity livestock farming areas are mainly located in western England, Ireland, and in parts of Germany and France whereas low-intensity livestock farming generally occurs throughout Europe but more pronounced in Scotland, central France and eastern Latvia. Low-intensity grasslands that are often under grazing use mainly occur in the northern part of Sweden, Scotland, and in the Mediterranean regions, particularly in Spain and on Sardinia.

Land systems dominated by high-intensity forests occurs in Aquitania (France), Galicia (Spain), central Portugal, southern Sweden and Finland, and more scattered in Germany, Austria, Poland, Slovakia, and the Czech Republic whereas low-intensity forests dominate in northern Europe and along mountainous regions across Europe (e.g.; Carpathian in Romania, Alp regions in France and Italy, Apennine in Italy).

High-intensity agricultural mosaics generally occur throughout central Europe such as Germany, the Netherlands, Belgium, France, and England. Land systems dominated by low-intensity mosaics do not exhibit a pronounced spatial pattern and are widespread and scattered across Europe.

Urban built-up is defined by over-proportional coverage by urban structures such as sealed surfaces, buildings, or urban infrastructure (roads, airports). The spatial patterns of this archetype depict the location of European agglomeration areas such as Paris, London, the Ruhr Area, Berlin, or Rome.

Text SI V-5: Description of spatial patterns of Archetypical Change Trajectories.

Land-system changes showing increases in permanent cropland yields occurred spatially distinct in eastern Germany, central Belgium, and parts of Austria and Italy. Yield increases on arable croplands occurred mainly in north-western France, northern Spain, and north-eastern Germany. Archetypical changes related to high-intensity arable cropland in terms of fertiliser input (i.e., medium to high fertiliser application) occurred spatially pronounced in western Poland, central Germany, the Po valley (Italy), and in northern and western France. In contrast, intensification of medium-intensity arable cropland in terms of fertiliser input (i.e., low to medium fertiliser application) occurred mainly in parts of Poland, Spain, Italy, Sweden, Slovakia, and Hungary.

Declining trends of arable cropland yields reveal distinct spatial patterns with occurrences in eastern France, north-western Ireland, western Poland, along the Carpathian Mountains (Romania), and in parts of Germany, the Czech Republic, Sweden, and Lithuania. Archetypical changes of de-intensification of high-intensity arable cropland in terms of fertiliser input (i.e., high to medium intensive fertiliser application) occurred predominantly in western Hungary and in several parts of the UK, France, Germany, Romania, Bulgaria, and Greece whereas de-intensification of medium-intensity arable cropland in terms of fertiliser input was mainly limited to Romania, Bulgaria, and Lithuania.

Yield declines on grasslands were located almost exclusively in eastern European countries, especially in Poland, the Czech Republic, Slovakia, and southern Romania. Archetypical changes related to de-intensification of high-intensity livestock farming (i.e., high to medium livestock density) occurred predominantly in northern France, northern and southern Germany, eastern Poland, western England, and in some parts in Austria, the Baltics, and Ireland. In contrast, de-intensification of medium-intensity livestock farming occurred mainly in central UK, eastern Germany, eastern Poland, Latvia, and in parts of France, Hungary, Spain, and Bulgaria.

The intensification of forestry predominantly occurred in central and southern Germany, Austria, Latvia, southern Sweden, and Finland, as well as parts of Poland and Slovakia. Archetypical changes related to forest expansion over grassland mainly occur in the northern part of Spain, the Italian Alps, Greece, and in parts of Estonia, Lithuania, Bulgaria, Ireland, and the UK. Trends of deforestation for agricultural expansion mainly occurred in several regions across the Iberian Peninsula. Cropland-grassland conversions were mostly located in Eastern Europe, eastern Germany, central Italy, Denmark, and in parts of France and the UK.

Conversions of croplands (especially permanent croplands) to forests and grasslands areas were almost exclusively located in the Mediterranean region, especially in south-western Spain, northern Portugal, southern France, and along the Italian coastline facing the Mediterranean Sea. Archetypical changes related to urban expansion did not reveal distinct spatial patterns but a widespread and scattered spatial distribution. Regions with more pronounced urban expansion are the Rhone-Alpes region (south-eastern France), the border region between the Netherlands and Belgium, and the coastlines of the Iberian Peninsula.

Regions without particularly pronounced changes (i.e., stability in land systems) were widespread across Europe and often present in forested (e.g., Scandinavia) and mountainous (e.g., Romania, Spain) regions but also throughout France, western Germany, Estonia, northern Scotland, eastern England, and in parts of Ireland, Lithuania, Hungary, and Greece.

Text SI V-6: Detailed descriptions of Land-System Archetypes (LSAs).

The detailed descriptions of each LSA contain (i) a map displaying the spatial distribution of the respective archetype across the study region (left panel), (ii) a bar plot with indicator characteristics that were used for labelling the respective archetype (upper right panel), and (iii) a detailed description of the respective archetype (lower right panel).

All bar plots build upon z-transformed values for each indicator to make them intercomparable. Hence, all plots should be interpreted as how many standard deviations a certain indicator deviates from its aggregate mean value within the respective archetype.

The archetype description summarises indicator characteristics per archetype and provides numbers on the aggregate mean value (Table SI V-3) and the de-standardised z-scores (Table SI V-6) allowing for an archetype characterisation based on values in each indicator's original measurement unit.

Indicator mean values for the year 2006 generally deviated from zero, some even substantially. Hence, z-scores do not necessarily refer to the presence or absence of an indicator in a given archetype. As an example, assuming the absence of an indicator in a given cluster due to its z-score value around zero may be misleading if the study area average is clearly above zero. Here, the z-score around zero only refers to that the indicator does not deviate much from the study area average.

Text SI V-7: Detailed descriptions of Archetypical Change Trajectories (ACTs).

Detailed descriptions of each ACT contain (i) a map displaying the spatial distribution of the respective archetype across the study region (left panel), (ii) a bar plot with indicator characteristics that were used for labelling the respective archetype (upper right panel), and (iii) a detailed description of the respective archetype (lower right panel).

All bar plots build upon z-transformed values for each indicator to make them intercomparable. Hence, all plots should be interpreted as how many standard deviations a certain indicator deviates from its aggregate mean value within the respective archetype.

The archetype description summarises indicator characteristics per archetype and provides numbers on the aggregate mean value (Table SI V-3) and the de-standardised z-scores (Table SI V-7) allowing for an archetype characterisation based on values in each indicator's original measurement unit.

Mean values of changes between 1990 and 2006 were only marginally deviating from zero. Hence, strong deviations from the mean trend can be characterised as gross increases (if positive) or decreases (if negative). However, in cases where the indicator mean value deviates from zero and change is only marginal, trends do not necessarily refer to changes expected from z-score values. As an example, above average (z-score) values of an indicator can actually refer to gross decreases if the aggregate mean is strongly negative. Here, positive z-scores indicate a positive deviance form the aggregate mean. Since the mean is negative, the actual de-standardised value characterising the archetype is negative (despite the positive z-score), but less pronounced compared to the aggregate mean.

Chapter VI: Synthesis

1 Summary

The overarching goal of this thesis was to gain a better understanding of land-system changes that took place in Europe over the last two and a half decades with a particular focus on land-use intensity. Europe's land system is characterised by large environmental, political, and socio-economic heterogeneity and a long-lasting land-use history, which resulted in high land-system diversity and multifaceted land-change pathways. Within the period that was studies in this thesis (1990 to 2010), Europe experienced several political (e.g., the dissolution of the Soviet Union), economic (e.g., the change from national currencies to the Euro), institutional (e.g., the accession of the New Member States to the European Union), and structural (e.g., the reforms of the Common Agricultural Policy framework) changes that arguably had consequences for Europe's land system. However, knowledge on how these conditions relate to the spatial patterns and rates of land-system change in Europe is currently limited.

This thesis employed different approaches to address this shortcoming in order to provide a better understanding of land-system change in Europe. *Mapping patterns* of land-use intensity changes across Europe based on aggregated statistical data allowed depicting the spatial variability of intensity indicators and locating regions of high and low as well as increasing and decreasing management intensity. Using this information, *regression analyses* were used to identify and subsequently quantify important broad-scale determinants of land-use intensity changes across Europe and to disaggregate wood production statistics. The *identification of archetypical patterns and trajectories* of land systems in Europe reduced their large inherent complexity and allowed to recognise regions of similar land-use patterns and changes in a consistent manner Insights gained from these analyses were used to answer the two research questions of this thesis.

<u>Research Question I</u>: *What are the spatial patterns of recent land-use intensity changes in Europe and which spatial determinants are most influential for these?*

Chapters II, III, and IV focussed on mapping patterns of land-use intensity changes for land-based production systems (i.e., forestry and agriculture) across Europe and identified their most important environmental or socio-economic determinants. Specifically, the focus was on investigating two indicators of forestry intensity (i.e., forest harvesting intensity expressed by the ratio between wood fellings and net annual increment, and wood production expressed as the volume of fellings per forest area), as well as two indicators of agricultural intensity (i.e., yields and nitrogen application for six major crop-type groups).

Chapter II and III showed that forest harvesting intensity (system intensity metric) and wood production (output intensity metric) did not exhibit clear temporal trends or variability over the 10-year study period, with exceptions after large-scale storm events and subsequent salvage logging. In contrast, spatial patterns of forest harvesting intensity and wood production varied strongly across Europe with high intensity levels in the southern parts of Sweden, Finland, and Germany as well as in several parts of France. However, spatial patterns of wood production were not necessarily related to those of forest harvesting intensity and several regions revealed marked differences with regard to the intensity level of both indicators, such as parts of the Czech Republic, Poland, and Switzerland or the central and southern parts of Sweden and Finland. In general, harvested timber volumes were well below the net increment in most regions in Europe, both annually and over the period studied. Exceptions were traditional wood-production regions, such as southern Sweden and Finland, Switzerland, or southwest France, where harvested timber volumes exceeded natural regrowth. Wood production tended to be high in locations with high ecosystem productivity, high share of tree species used for roundwood production (pine, spruce, and plantation species), and low topographic heterogeneity. Similarly, forest harvesting intensity was high in locations with a large share of plantation species, low topographic heterogeneity, and mature stands. Country-specific characteristics (e.g., forest legislation/policies, ownership structure, fire or storm events) were also strongly related to forest harvesting intensity patterns. Regression-based downscaling of wood production statistics with a suite of spatial determinants allowed for a spatially explicit assessment of wood production levels and variability and outperformed traditional disaggregation approaches based on forest cover only.

Chapter IV showed that total crop yields (output intensity metric) increased by approximately 10% across Europe within our study period (1990-2007), while mineral nitrogen application (input intensity metric) decreased by approximately 10%. Intensity levels and changes varied temporally and spatially across crop-type groups and indicators. Yields from industrial and labour-intensive crops increased most strongly and had yield levels > 25 t/ha, whereas trends of cereal crops and oilseeds and pulses were stable at yield levels ~5 t/ha. Nitrogen application for fodder and permanent crops decreased strongest but had the lowest application rates (< 50 kg/ha), while trends for industrial, labour-intensive, and cereal crops were relatively stable at high application levels (> 100 kg/ha). Generally, high agricultural intensity occurred in Western Europe compared to lower-intensive use in the remaining parts, especially Eastern Europe. Contrary to Europe-wide trends, some countries showed stable (e.g., Netherlands or Denmark) or declining (e.g., Bulgaria or Poland) crop yields, respectively stable (e.g., Sweden or Spain) or increasing (e.g., Poland or Slovakia) nitrogen application rates. Most regions in Europe were characterised by a single high-intensive indicator, except regions in France, Germany, and the Netherlands that had high intensity levels for both, yields and nitrogen application. Higher yields were generally related to higher expenses for and application of nitrogen, higher farm economic performance, and advantageous hydrologic conditions (i.e., higher soil water availability for plants and annual precipitation). Higher nitrogen application was generally related to higher crop specialisation, better farm economic performance, and better soil quality (i.e., higher soil organic carbon content and water availability for plants). Growing degree days were majorly negatively related to both agricultural intensity indicators.

<u>Research Question II</u>: Where are similar patterns and change trajectories of land systems in Europe located and what are their characteristics?

Chapter V focussed on mapping and characterising Europe's land system in a spatially and thematically consistent way by identifying regions that revealed similar, or archetypical, patterns and trajectories of land-use extent and intensity indicators. The analysis yielded spatially explicit maps of 15 Land-System Archetypes (LSAs) for the year 2006 and 17 Archetypical Change Trajectories (ACTs) between 1990 and 2006 across Europe and six key findings emerged from these results. First, long-term land-use legacies were still apparent in the current spatial patterns of European land systems as path-dependent effects of former land management. Second, Europe was characterised by a distinct east-west divide in terms of land-use intensity, with high-intensity areas mainly located in Western and Central Europe in contrast to medium/low-intensity area in Eastern Europe (see also Appendix A). Third, despite technological innovations to compensate for disadvantageous site conditions, agro-climatic conditions were an important determinant of land-system patterns in Europe and high-intensity systems mostly occurred in locations with favourable edaphic and climatic conditions. Fourth, Europe's land system was strongly characterised by stable land-use patterns between 1990 and 2006. In regions of change, increasing or stable yields on shrinking cropland area were common, indicating polarisation trends that go along with rural population declines and (peri-)urbanisation (see also Appendix A). Fifth, forestry intensification mainly took place in traditional wood production regions (Germany, Northern Europe, Baltics), while forest area expansion occurred largely in

Southern Europe and was related to afforestation and forest encroachment on abandoned agricultural land. Sixth, urbanisation trends occurred mainly along the coasts and around urban agglomeration areas, especially in Western Europe, and often went along with abandonment and declining land-use intensity in the hinterlands.

2 Main conclusions and implications

2.1 Main conclusions

The results from each core research chapter provided answers to the two research questions of this thesis. Based on these results, five cross-cutting insights emerged that facilitate a better understanding of the spatial patterns of land-system change in Europe and thus address the overarching goal of this thesis.

First, the assessment of patterns and changes of land-use intensity emphasised the importance of considering the multidimensionality of land-use intensity (cf. Chapter II-IV). Different indicators of land-use intensity can have divergent spatial patterns that may lead to inaccuracies when characterising locations in terms of their management intensity. For analysing land-use intensity, the consideration of its multidimensionality has been recently advocated (Erb et al. 2013a) and the results from this thesis support this suggestion. In Europe's forestry systems, the spatial patterns of output metrics (i.e., wood production) and system metrics (i.e., felling-to-increment ratio) of land-use intensity revealed partly strong variability as regions characterised by high forest harvesting intensity were not necessarily regions of high wood production (cf. Chapter II and III). A similar picture emerged for agricultural systems, for which input metrics (i.e., fertiliser application) and output metrics (i.e., crop yields) of land-use intensity exhibited marked spatial variability and divergence (cf. Chapter IV). These findings are further supported by the results presented in Appendix A, showing that land conversions (as an input for land-based production) and intensity changes revealed distinct spatial patterns across Europe, partly characterised by polarisation trends within regions (i.e., area decline and intensity increase). Hence, characterising land-use intensity at a given location has to account explicitly for the indicators that have and especially those that have not been used. This has implications for analyses that address impacts and trade-offs of land-use intensity as intensity indicators can be heterogeneously distributed across space, thus impeding the generalisation of outcomes from single intensity metrics (cf. Chapter VI:2.2).

Second, the assessment of the most important spatial determinants that explain patterns and changes of land-use intensity in Europe revealed that different intensity indicators were related to specific sets of spatial determinants, thereby reflecting the multidimensionality of land-use intensity. Generally, both socio-economic and environmental factors were influential in explaining land-use intensity patterns. Especially edaphic and climatic conditions remained strong determinants of land-use intensity (cf. Chapter IV and V), despite technological innovation and substantial investments into overcoming agro-climatic limitations, such as irrigation techniques or specialised crop varieties (Peltonen-Sainio et al. 2009, Ewert et al. 2005). However, the structural differences between forestry and agricultural systems (e.g., long vs short production cycles, marginal vs. fertile sites) were underlined by different determinants dominantly related to the investigated intensity indicators. Soil quality and economic competitiveness were of major importance for explaining agricultural intensity, while forest resource conditions and accessibility were the most important determinants of forestry intensity. This suggests that specific requirements on site conditions strongly shape the intensity levels of a particular production system. Beside these pan-European patterns, country-specific characteristic were markedly related to intensity levels. This suggests that despite Europe-wide policies and regulations, national legislations, policies, and traditions are important factors to consider for broad-scale, transnational land-use intensity assessments.

Third, the combination of patterns and changes of land-use extent and intensity with their spatial determinants allowed a spatially and thematically consistent assessment of the state and pathways of Europe's land system. Most strikingly, much of Europe's land system showed strong signs of stability in extent and intensity of land use, while (de-) intensification trends were only of minor importance (cf. Chapter V and Appendix A). This is somewhat surprising, considering the marked institutional, structural, and economic changes, as well as several policy reforms in the agricultural and forestry sector in Europe between 1990 and 2010. Apparently, the relatively robust land-system patterns over large parts of Europe (cf. Chapter V) represent still prevailing long-lasting land-use legacies and histories in Europe's land-system. In forestry, traditional wood-producing regions evolved with the early replacement of natural deciduous by coniferous tree species for the sake of intensive timber production, which led to a path dependency for these regions. Further, long rotation lengths and management cycles likely translated into observed stable forest management patterns (cf. Chapter II and III). In agriculture, it can be assumed that subsidies from the European Union targeting at maintaining the current configuration of

Europe's land system (e.g., payments from Pillar II of the Common Agricultural Policy (CAP); cf. Chapter V) indeed had stabilising effects.

Fourth, a distinct east-west divide was found in Europe's land system patterns and trajectories, with intensively used and intensifying regions particularly located in Western Europe (cf. Chapter II-V). These patterns were seconded by the results of Appendix A that exhibited hotspots of increasing agricultural extent and intensity mainly in Western Europe, in contrast to decreasing trends in Eastern Europe. This spatial divide, however, was strongly related to the agricultural sector as many regions in Europe's east exhibited intensively managed forests (cf. Chapter II-IV). A potential reason for this sectoral difference is that Western European countries, compared to Europe's east, generally experienced an earlier start of agricultural industrialisation, had access to Common Agricultural Policy (CAP) payments, and were not affected by the structural and market changes following the breakdown of the Soviet Union (Kuemmerle et al. 2015, Jepsen et al. 2015), whereas forest management intensity was at similar levels in Europe's east and west during this period (Forest Europe et al. 2011). Although the apparent east-west divide resembles knowledge already gained on broader scales (Jepsen et al. 2015), this thesis provides spatially explicit information on where areas of high/low intensity are located and which regions are characterised by similar land-system patterns and trajectories, thereby particularly accounting for transnational trends (e.g., agricultural abandonment, forest transition).

Fifth, parts of the analyses carried out in this thesis demonstrate the power of machine learning techniques in investigating land-system patterns and changes across broad geographic scales (cf. Müller et al. 2013, Lakes et al. 2009, Gellrich et al. 2008). With regard to regression analyses, traditional approaches of modelling patterns and changes in land-system science often rely on statistical models, such as logistic regressions. Due to their strong assumptions on data distributions, limited ability to model non-linearity and variable interactions, as well as variable selections based on null hypothesis significance testing, these techniques hamper the investigation of the complex relationships present in land systems. Algorithmic models, such as Boosted Regression Trees, alleviate these limitations and proved to be a valuable tool for explaining land-use intensity phenomena. Especially their efficient variable selection abilities and their continuous results in terms of the importance of land-change determinants, in contrast to null hypothesis significance testing, allowed for an informative identification of determinants and quantification of their influence. Furthermore, partial dependency plots that depict the marginal effect of these determinants on land-use intensity indicators provided more nuanced information on their relationship compared to traditional regression coefficients. In case of non-linear relationships, threshold or optima values could be detected for determinants and traced back to their spatial patterns, which allowed for a spatially explicit identification of regions where determinants were found to be related to high/low land-use intensity. The data-driven, unsupervised clustering algorithm used in this thesis (Self-Organising Maps) was especially suited for multidimensional scaling (i.e., reducing the complexity) in land-systems due to its topology-preserving abilities. Based on a neighbourhood function, existing topologies in input space (i.e., indicators of land-use extent and intensity) are maintained, providing a major advantage for the analysis of spatial phenomena compared to traditional approaches such as PCA or k-means clustering.

2.2 Implications

The results of this thesis have the potential to contribute to scientific and policy-related actions that aim at guiding land systems in Europe to a more sustainable use. Considering the already high intensive use of much of Europe’s land system (Haberl et al. 2007) and the substantial impacts on Europe’s landscapes that go along with this as well as the increasing demand for land-based products, pursuing a more sustainable future land use in Europe is imperative (Pedroli et al. 2015). The European Union addressed this issue by advocating a “Roadmap to Resource Efficient Europe” that targets, for example, the avoidance of further land take, the halt of biodiversity loss and ecosystem degradation, or the reorganisation of land-use policies such as the Common Agricultural Policy (CAP) (EC 2011). In light of this need to manage Europe’s natural capital in a way that ensures ecosystem service provisioning in the future, three visions of future sustainable land use in Europe have been recently identified (Pedroli et al. 2015): (i) “Best Land in Europe” aiming at an optimal use of land resources, (ii) “Regional Connected” aiming at living closer to the natural environment, and (iii) “Local Multifunctional” aiming at self-sufficiency of local communities. As these visions are not necessarily compatible and their attainment will entail trade-offs under current socio-economic and policy conditions (Pedroli et al. 2015), decision makers need profound information on spatial patterns, changes, and determinants of land-system change for designing and implementing nuanced, effective, and spatially targeted actions to ensure the future sustainability of land use in Europe with respect to the set goals and visions.

Although the achievement of sustainable land use in Europe likely requires a broader, multi/interdisciplinary, and more holistic approach compared to the one taken within this thesis, the outcomes of thesis offer valuable inputs for and links to specific applications and different research fields that can foster land-system understanding in order to realise a sustainable future of land use in Europe. First, current policies, such as CAP, are mostly designed as one-size-fits-all measures. Contrary, the results of this thesis support localised information on land systems in Europe with regards to their patterns, changes, and determinants, with a special focus on land-use intensity. Regions characterised by similar land-system patterns or trajectories provide information where similar policy tools can potentially be valuable to develop regionalised and context-specific land-management strategies. Such information is urgently needed to address the call for regionalised and targeted policy solutions, considering country- or regional-scale differences that can result in specific policy requirements (cf. Gorton et al. 2009). Second, the results of this thesis allow for a better assessment of land-use impacts with regard to ecosystem services (e.g., biodiversity or carbon sequestration) but also to human societies (e.g., rural depopulation due to land-use polarisation). For example, areas of overly high land-use intensity, for example where excess nitrogen is common, can be identified, which could be used in the context of developing regional strategies to lower land-use pressure. Third, the results of this thesis allow the identification of areas with potential for intensifying land-based production. This information can serve as an input for multi criteria and trade-off (or landscape optimisation) analyses that seek to create synergies between land-based production and environmental protection in order to identify potential solutions for a more sustainable (intensification of) land use with regards to the indicators studied (for example agricultural yields and biodiversity; cf. Macchi et al. 2015, Phalan et al. 2011). Fourth, resulting maps from this thesis can serve as input layers for refining quantitative and spatial analyses of related research fields, such as species distribution models, carbon bookkeeping models, climate models, Dynamic Global Vegetation Models (DGVMs), or land resource related models (e.g., EFISCEN). By incorporating information on land-use intensity patterns and changes, such analyses could be improved by moving beyond the commonly applied utilisation of mere land-use categories as representations of human land-use activities.

3 Outlook

This thesis advanced the understanding of recent land-system changes in Europe by mapping patterns and changes of several land-use intensity indicators and assessing their determinants by applying a suite of regression techniques on the one hand and identifying and characterising archetypical patterns and trajectories of land systems on the other. However, some important topics for future research emerged during the course of this thesis that were beyond the scope of this work.

During the course of this thesis, assessments of nitrogen use efficiency (i.e., yield-fertiliser ration) gained importance (Lassaletta et al. 2014, Conant et al. 2013). Although the application of nitrogen fertilisers over the past decades allowed for a substantial increase in crop production, it also entailed massive environmental impacts. Assessing nitrogen use efficiency allows the analysis of agronomical and environmental performances of cropping systems and to evaluate excess nitrogen application (Lassaletta et al. 2014). Existing studies so far relied on country-level data on yields and nitrogen application. Using sub-national data for both indicators (cf. Chapter IV) would allow assessing patterns and changes of nitrogen use efficiency with greater spatial detail and identifying important determinants related to these. Knowledge on both, patterns and determinants, can lead to the identification of regions with poor nitrogen use efficiency (i.e., with high excess nitrogen) and consequently high environmental impacts of land use that may serve as candidate regions to lower land-use impacts in order to achieve more sustainable land use.

The assessment of influential factors for land-use intensity patterns and changes could benefit from expanding the suite of explanatory factors to the inclusion of information closer to actual drivers of land change. For example, the increasing role of international trade has strong implications for national and regional supply with land-based products (Kastner et al. 2015, Kastner et al. 2011). As Europe exhibits a large and growing dependency on imports of land-based products and consequently exports its land footprint to regions of production (EEA 2014, Khatun 2012), incorporating information on these telecouplings may foster the understanding of land change within Europe's boundaries. Possible options for this include the utilisation of the embodied human appropriation of net primary production (eHANPP, Kastner et al. 2015) or import/export balances of land-based products as predictors in regression analyses.

Further, rapid and fundamental changes in boundary conditions for land management arguably influenced Europe's land systems, for example the breakdown of the Soviet

Union (Kuemmerle et al. 2008, Kuemmerle et al. 2007) and the introduction and modification of policies such as the Common Agricultural Policy (CAP) (Lefebvre et al. 2012, Schmid and Sinabell 2007). Isolating the effect of these single events can be difficult using regression analyses with dummy variables representing the presence or absence of such events. Quasi-experimental methods, such as matching statistics (Baumann et al. 2014), could be employed to isolate the spatially different effects of such natural experiments on land system in Europe and approach a more causal explanation for observed patterns and changes. Knowledge gained from these analyses could be used to evaluate the success/impacts of policies and generally to better understand the effects of such drastic changes in boundary conditions on land systems.

The assessment of archetypical patterns and trajectories of land systems could be improved by additionally including the cultural dimension of land systems. By relying on biophysical and productive properties of land change, the archetype approach used in this thesis did not account for cultural characteristics eminent in coupled human-environment systems. Cultural landscapes are not only important suppliers of provisioning ecosystem services, but also harbour a range of non-material landscape values (Schaich et al. 2010), such as aesthetic value (van Zanten et al. 2014) or cultural identity (Waterton 2005), that need to be addressed in European land-system research (Plieninger et al. 2014). Further, projecting land-change trajectories into the future and evaluating the effect of different policy scenarios on the European land system can provide valuable knowledge to inform policy makers about the spatial configuration of and pathways to future land systems in Europe. This topic was recently addressed by Stürck et al. (2015) with a rule-based approach relying on expert knowledge to identify and map future land-system pathways using a suite of different policy scenario projections. This approach could be supplemented by applying a data-driven approach, which would allow for identifying land-change pathways that were not predefined by a-priori rule sets, or expanded by using climate scenarios to account for future impacts of climate change on land systems.

With regard to the data sets used in this thesis, future research may focus on two main issues that were not addressed in this thesis. First, this thesis relied to some extent on land-cover data from the Coordination of Information on the Environment (CORINE) and on official national statistics available from the Eurostat database, which restricted the temporal and spatial coverage of this work. At the time of writing, CORINE data was only available for the years 1990, 2000, and 2006 and land-cover data for the year 2012 is still in preparation. Future assessments of land-system changes in Europe would tremendously benefit from extending the study period until 2012 to capture important events such as the financial crisis of 2008 and its legacies that arguably shaped the state of Europe's land system (Petrick and Kloss 2013). Due to the accession of the New Member States to the European Union only in 2004 and 2007, data was often not available for previous years and some countries had to be excluded from the analyses. To provide a more complete and nuanced picture of Europe's land-system changes, efforts to fill these gaps would be of high importance. Moreover, consistently including non-EU countries such as Norway and Switzerland would allow assessing land-system changes on a pan-European scale.

Second, the spatial detail of this thesis varied between analyses on aggregated (patterns, changes, and drivers of land-use intensity) and pixel (archetypes) level. Aggregated data have several shortcomings, including the inability to represent sub-regional differences in land-use intensity indicators, the proneness to contain a substantial amount of missing data, or varying data quality across regions. However, spatially explicit data on land-use intensity is scarce for Europe and existing data sets are often based on dasymetric mapping (e.g., Verkerk et al. 2015, Temme and Verburg 2011, Neumann et al. 2009) or derived from interpolation of ground observations (e.g., van der Zanden et al. 2013). Remote-sensing based indicators of land-use intensity allow for an independent and spatially explicit measurement of land-use intensity (Kuemmerle et al. 2009), but these indicators are often temporally restricted (e.g., Fritz et al. 2015, Siebert et al. 2010). A new generation of spatially explicit time series of land-use intensity indicators is currently under development, with particular focus on agricultural areas, that expand the suite of intensity indicators (Estel et al. 2016, Estel et al. in preparation). Using these data, future assessments of determinants of patterns and changes in land-use intensity will provide more spatially detailed information, can account for sub-regional differences in both, target and predictor variables, and alleviate the potential limitations of this thesis with regard to spatial detail and indicators used.

Methodically, the analyses carried out in this thesis employed state-of-the-art regression and cluster techniques. Due to their excellent properties for identifying and understanding determinants of land change, algorithmic models may well serve as a preferable choice for future analyses related to land-system science. However, in light of the increasing focus on spatially explicit data on land-use intensity, models that account for and incorporate spatial data features such as target spatial autocorrelation, predictor non-stationarity, or spatio-temporal variability would further advance the understanding of land systems as these features reveal space-time effects on observed patterns or changes. Existing methods usually neglect or correct for these features (e.g., through minimum-distance sampling to correct for target spatial autocorrelation) or focus only on a single feature (e.g., Brunsdon et al. 1996, Crase et al. 2012), thereby inadequately or only indirectly reflecting spatial properties of land change. For example, land-use intensity (changes) may be positively related to a certain spatial determinant in some parts of the study area, but only marginally or even negatively related elsewhere. A method addressing these shortcomings is Model-Based Boosting (Hothorn et al. 2011), which has been applied to ecological phenomena and is a promising option for land-system related analyses. As this method is designed for pixel-based analysis, it could not have been applied to the administrative-unit level data this thesis relies on. Hence, future fields of research embrace methodical advances to enable this approach to handle spatially aggregated data on the one hand, and thematic advances to use prospective spatially explicit data on land-use intensity on the other. Another interesting strand of research includes the application of agent-based models (ABMs) for broad-scale assessments of factors that influence land-use decisions by different actors. Using this bottom-up approach could provide deeper insights into how individual land-use decisions also drive land-system change in Europe, which could not been accomplished within the framework of this thesis.

Europe looks back at a rich history of land use and land-use changes influenced by several political, structural, and institutional changes that led to great land-system diversity. Prospectively, Europe will face several changes over shorter and longer terms that will likely affect the future state of Europe’s land system, such as policy adaptations, for example the CAP reform of 2013 with changes in the Direct Payments and Rural Developments strategies, the recently achieved UNFCCC COP21 agreement to limit global warming to less than 2 degrees and to substantially reduce greenhouse gas emissions, or the further accession of new member states to the European Union. The outcomes, implications, and outlooks that emerged from this thesis foster knowledge on past and current land-system patterns, changes, and determinants to better understand Europe’s complex human-environment system. Ultimately, this knowledge can help to address future challenges for Europe’s land system and to guide Europe to a more sustainable future land use.

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Appendix A:
Hotspots of land-use change in Europe

Environmental Research Letters (in review)

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Abstract

Assessing the spatial patterns of land conversions and management intensity changes is crucial to understanding land-system trajectories and their environmental and social outcomes. Yet, patterns of changes in land management intensity, and thus our understanding of how management intensity changes relate to land conversions, remain unclear for many world regions. We compiled and analysed a set of land change indicators for Europe for the period between 1990 and 2006, pertaining to land conversions and changes in management intensity. We assessed recent trajectories, identify hotspots, and explore spatial concordance of land change processes. We found a clear East-West agricultural divide, with stronger cropland declines in the East, and generally lower management intensity in the East compared to the West, likely as a result of the breakdown of socialism, 20th century land-use legacies and the Common Agricultural Policy. We also identified diverging trends of intensification in areas highly suitable for farming, and disintensification and cropland contraction in more marginal areas, likely a result of the ongoing structural changes in Europe's rural areas. Despite the overall moderate rates of change, many regions in Europe fell into at least one land-change hotspot during the study period, influenced by polarisation processes (co-occurring area decline and intensification or co-occurring area increase and disintensification). Our analyses highlight the diverse patterns of land-change trends and hotspots in Europe, and the importance of jointly considering land conversions and management intensity changes and assessing land-change feedbacks across sectors. In order to steer land use change towards desired futures, we highlight the need for more context-specific land-use policies that consider regional differences in land-system trends.

1 Introduction

Humankind depends on land use for food, feed, and bioenergy, yet the environmental trade-offs of land use are substantial – from local to global scales (Foley et al. 2005, MA 2005a, Tilman et al. 2011). Understanding where, how, and why land use is changing is thus important for mitigating these trade-offs, and for developing policies to transition to more sustainable forms of land management (Turner et al. 2007, Rounsevell et al. 2012). In this context, land-change science has so far predominantly focused on land conversions, including deforestation (e.g., Geist and Lambin 2002, Hansen et al. 2013, Graesser et al. 2015), urbanisation (e.g., Deng et al. 2008, Taubenböck et al. 2012), or forest expansion (e.g., Rudel et al. 2005, Meyfroidt and Lambin 2011). Changes in land-management intensity (e.g., agricultural intensification, logging intensity) have received much less attention (Erb et al. 2013a), although intensity changes have long been widespread (Ellis et al. 2013), are the dominating land change processes in some regions (Rudel et al. 2009, Rounsevell et al. 2012), and will likely increase in their importance as land scarcity increases (Foley et al. 2011, Lambin and Meyfroidt 2011). Yet, assessing the spatial patterns of intensity changes hinges on adequate spatial data on management intensity for large areas (Verburg et al. 2011, Kuemmerle et al. 2013).

Important links between land conversions and intensity changes in land systems are also increasingly emerging, with multidirectional and spatially heterogeneous trends frequently found. For example, agricultural intensification may result in the concentration of agriculture on fertile soils and the abandonment of more marginal land (Stoate et al. 2009, Piquer-Rodríguez et al. 2012, Niedertscheider et al. 2014) or, conversely, in the expansion of land use through rebound effects (Lambin and Meyfroidt 2011, Gasparri and le Polain de Waroux 2014). Similarly, urbanisation is a powerful driver in reorganising land-use systems, leading to agricultural intensification close to cities, and reduced land-use pressure in the surrounding hinterland (Aide and Grau 2004, Seto et al. 2012). As globalisation connects land systems across large distances, spatially disparate linkages between area and intensity changes may also occur. An example for this is the increasing spatial disconnect between production and consumption that may allow land in one region to be set-aside while the land-use footprint embodied in traded goods increases elsewhere (Mayer et al. 2005, Lambin and Meyfroidt 2011, Lenzen et al. 2012, Kastner et al. 2014). While these examples highlight the importance of jointly analysing land conversions and intensity changes, our understanding of how spatial patterns in these land-change processes relate to each other, or how changes in one sector (e.g., agriculture) relate to changes in another (e.g., forestry, urban areas) remains weak.

During the second half of the 20th century, European land use has predominantly changed along intensification gradients (Rounsevell et al. 2012). Agricultural systems were intensified substantially, especially during the 1960s to 1980s, and Europe today has some of the most intensively managed croplands in the world (Haberl et al. 2007, Mueller et al. 2012). On the other hand, farmland area has declined in areas less suitable for agriculture, partly due to a declining profitability of farming and rural emigration (MacDonald et al. 2000, Navarro and Pereira 2012). This triggered the widespread loss of traditional agricultural landscapes (Fischer et al. 2012) and, together with active afforestation efforts, has increased overall forest area since the 1950's (Gold et al. 2006, Fuchs et al. 2013). The structure of Europe's forests has also changed, including substantial increases in growing stock and increment (Gold et al. 2006, Rautiainen et al. 2010), due to changes in forest management, nitrogen deposition, and climate change (Erb et al. 2013b, Fernández-Martínez et al. 2014, Pretzsch et al. 2014). Finally, Europe expanded its conservation network substantially (Jones-Walters and Čivić 2013), and concerns about the environmental costs of intensification have resulted in a growing emphasis on multifunctionality, for example through agri-environmental and set-aside schemes (Whittingham 2011).

Where these different land-change processes occur and how their spatial patterns relate to each other has not been systematically studied. Only a few studies have observed land conversions at the pan-European scale, either relying on small case study regions (Gerard et al. 2010) or solely on the Coordinated Information on the European Environment (CORINE) land-cover product (Büttner et al. 2004, Feranec et al. 2007, Hatna and Bakker 2011, Fuchs et al. 2013). While CORINE captures some changes in broad land-cover classes relatively well (e.g., urbanisation), estimates for some key land-use change processes, for example farmland abandonment or deforestation (which is confused with clear-cutting in CORINE) are uncertain. Finally, rates and patterns of changes in the management intensity of agriculture and forestry are not captured by CORINE (Stoate et al. 2009). New spatially-explicit, land-use datasets have recently become available (Neumann et al. 2009, Temme and Verburg 2011, Levers et al. 2014, Overmars et al. 2014, Plutzar et al. 2015, Verkerk et al. 2015), providing new opportunities to better understand the relationship among different land-change processes in Europe.

Our overarching goal was to understand the spatial patterns of land conversions and management intensity changes in Europe's agriculture, forestry, and urban areas in order to identify land-change hotspots and to assess the spatial congruence between land-change processes. Specifically, we asked the following research questions:

1. What was the spatial pattern of changes in the extent and intensity of agriculture, forestry, and urban areas in Europe since between 1990 and 2006?
2. Where are hotspots and coldspots of these land changes in Europe?
3. How do spatial patterns of these land use changes relate to each other?

2 Methods and Materials

2.1 Datasets used

Our study region was the EU excluding Cyprus, Malta, and Croatia. We gathered data on changes in the extent and intensity of agriculture, grazing, and forestry, as well as information on changes in the extent of urban areas (Table A-1). A critical issue when jointly analysing area and intensity changes is consistency between datasets. We therefore drew from land-use statistics from the Common Agricultural Policy Regionalised Impact (CAPRI) database (Leip et al. 2008, Britz and Leip 2009) that we disaggregated to a target resolution of 3x3 km² (see below and Text SI A-1 in the Supplementary Information for details). Datasets that were available at a finer scale were aggregated to this common resolution. Our target time period was 1990 until 2006, the most recent year for which the majority of our datasets were available (see below and Text SI A-1 and Text SI A-2).

Table A-1: Indicators of land-use change indicators considered in the analyses to characterise land-system change in Europe for the time period 1990-2000-2006 (-2010).

	Area change	*Intensity change*
Cropland	Cropland area change (arable cropland and permanent cropland) Fallow and abandoned land (farmland abandonment, and farmland recultivation)	Changes in input intensity (fertiliser) Changes in output intensity (yield changes for major crops)
Grazing land	Pasture/grassland area change	Changes in input intensity (livestock units) Changes in output intensity (biomass removal from grazing land)
Forestry	Forestland area change	Changes in output intensity (harvesting volume)
Urban areas	Urban extent change	---

Data on area changes

We used cropland and pasture area from the CAPRI database (Leip et al. 2008, Britz and Leip 2009) for the years 1990 and 2006 (i.e., corresponding with the CORINE time periods) at the NUTS-2 (Nomenclature des unités territoriales statistiques) level. We allocated cropland area (i.e., arable land and permanent crops) and pasture area to the 3x3 km^2 grid cells using the CORINE cropland and the CAPRI-DynaSpat layers (Leip et al. 2008, Heckelei and Kempen 2011) as weights. We also allocated pastures to the CORINE classes 'heterogeneous agricultural area', as well as 'shrublands and 'grasslands' in NUTS-2 regions where not all pasture area could be allocated.

Farmland abandonment is poorly captured by CORINE (Verburg et al. 2009), and we therefore mapped indicators for farmland abandonment and recultivation from MODIS Normalised Differenced Vegetation Index (231m) time series from 2000 to 2012 (Estel et al. 2015). For each year, we classified each MODIS pixel that fell within the CORINE cropland and pastures classes as either managed (i.e., ploughed, mowed or grazed) or fallow. Using the resulting managed/fallow time series, we then defined agricultural abandonment and recultivation and summarised these classes at the 3-km grid level (see Text SI A-1 in the Supplementary Information).

Assessing changes in forestland from satellite-based land-cover maps such as CORINE is challenging, because forest cover changes can reflect permanent gains or losses in forestland, but also natural disturbance (e.g., storms or fire) or management (e.g., harvest), which do not reflect land-use change. To derive forestland maps, we disaggregated harmonised, regional-level forestland statistics for the years 1990 and 2005 to the 3-km grid using CORINE forest cover as weights (Levers et al. 2014, Plutzar et al. 2015). To calculate the extent of urban area change, we relied on the 1990 and 2006 CORINE maps and calculated percent urban land cover within 3x3 km^2 cells based on the 11 urban or built-up classes.

Data on intensity changes

To measure land-management intensity, we used two types of complementary metrics, following Erb et al. (2013a) and Kuemmerle et al. (2013): (i) input metrics, which measure inputs to production, usually per land area (e.g., fertiliser, pesticides, labour), and (ii) output metrics, which relate outputs to inputs (e.g., yields, felling-to-increment ratio). In terms of cropland inputs, we used an existing set of maps based on homogenised fertiliser use data from the CAPRI database, which first was classified into three fertiliser input classes (low: <50 kg/ha, medium: 50-150 kg/ha, and high: >150 kg/ha), and then was downscaled to a 1-km grid level (Temme and Verburg 2011, Overmars et al. 2014). For the purpose of this study, these data were then aggregated to our target resolution of 3-km (see Text SI A-2 in the Supplementary Information). In terms of cropland outputs, we used yields for the 13 most important crops from the CAPRI database for 1990 and 2006 and disaggregated these yields to the 3-km target grid, using crop-specific suitability maps derived using a niche modelling approach (see Text SI A-2 in the Supplementary Information).

Regarding grazing systems, we derived grazing intensity (measured as livestock units (LSU) per pasture area) by using NUTS-2 level livestock numbers to calculate equivalent LSU for the years 1990, 2000, and 2006, and then downscaled these data following Neumann et al. (2009) to a 1-km grid. We then categorised the resulting livestock densities into four grazing intensity categories (1: <25 LSU/km^2; 2: 25-50 LSU/km^2; 3: 50-100 LSU/km^2; and 4: >100 LSU/km^2) and aggregated them to our target grid. Regarding output metrics, we used biomass yields (i.e., biomass removed from pastures) from CAPRI, disaggregated to our target grid, using a combination of actual net primary production (NPP) and slope as weights (see Text SI A-2 in the Supplementary Information).

To assess forestry intensity, we compiled harmonised, annual wood removal maps, based on regional harvest statistics from 2000 to 2006 at the level of administrative units (Levers et al. 2014). We disaggregated these wood removal statistics using harvest likelihood as weights (Verkerk et al. 2015) to the target resolution of 3x3km. To extend the time period covered, we disaggregated national-level harvesting data from Forest Europe et al. (2011) for 1990, assuming constant harvesting ratios among regions within a country, which is supported by the very stable harvesting patterns found by Levers et al. (2014) (see Text SI A-2 in the Supplementary Information).

2.2 Analysing spatial patterns of land change in Europe

Using the database of area and intensity changes described above, we calculated absolute change values on a per pixel basis by subtracting the 2006 from the 1990 time period. Calculating change in the original data range (rather than as % change relative to 1990) avoids incorrectly labelling areas as hotspots which have undergone high relative changes, but comprise insignificant areas or amounts of respective land-use change. To map hotspots, we derived quantile maps per indicator, classifying all positive and negative values into 5% and 10% bins. We selected the top bins with the highest amount of positive and negative change per indicator as hotspots of increase and decrease, respectively. Bins with the lowest amount of positive and negative change, plus all unchanged areas, were categorised as coldspots (i.e., areas of stability).

To summarise across indicators, we counted how often a grid cell was included in a hotspot or coldspot for the cropland, pasture, and forestry indicators separately, and for area change and management intensity change indicators separately. To highlight spatial patterns of area changes relative to intensity changes, we derived two-dimensional concordance maps for our cropland, pasture and forestry indicators. Finally, we quantified the spatial associations between area and intensity change using local indicators of spatial association (Anselin 1995). We used the bivariate Moran's *I*, which measures the strength of the relationship between the two variables and identifies significant clusters ($p<0.05$, 999 permutations) of (i) increasing area and increasing intensity, (ii) increasing area but declining intensity, (iii) decreasing area and increasing intensity, and (iv) declining area and declining intensity.

3 Results

3.1 Area changes among broad land use categories

The most widespread conversions among broad land-use types in the EU between 1990 and 2006 were cropland decline (~129.630 km^2), followed by expansion of grassland (~75,670 km^2), and forest areas (~70,630 km^2). The least common conversions among broad land-use categories were declines in the area of permanent crops (~16,930 km^2) and urban expansion (~16,820 km^2). Farmland (cropland and pastures) abandonment amounted to 20,500 km^2 between 2000-2012, whereas recultivation after 2006 affected 16,430 km^2. At the European scale, these area changes translated into moderate land-conversion rates in the agricultural sector between 1990 and 2006, ranging from -13.4% for permanent crops to 6.5% for grasslands. In this period, urban expansion revealed marked changes with approximately 21% increase in urban built-up cover.

Land conversions after 1990 showed distinct spatial patterns across Europe (Figure A-1). While cropland declined slightly throughout much of the EU, hotspots occurred mainly in Eastern Europe (e.g., eastern Poland, Czech Republic, Romania, Bulgaria) and the

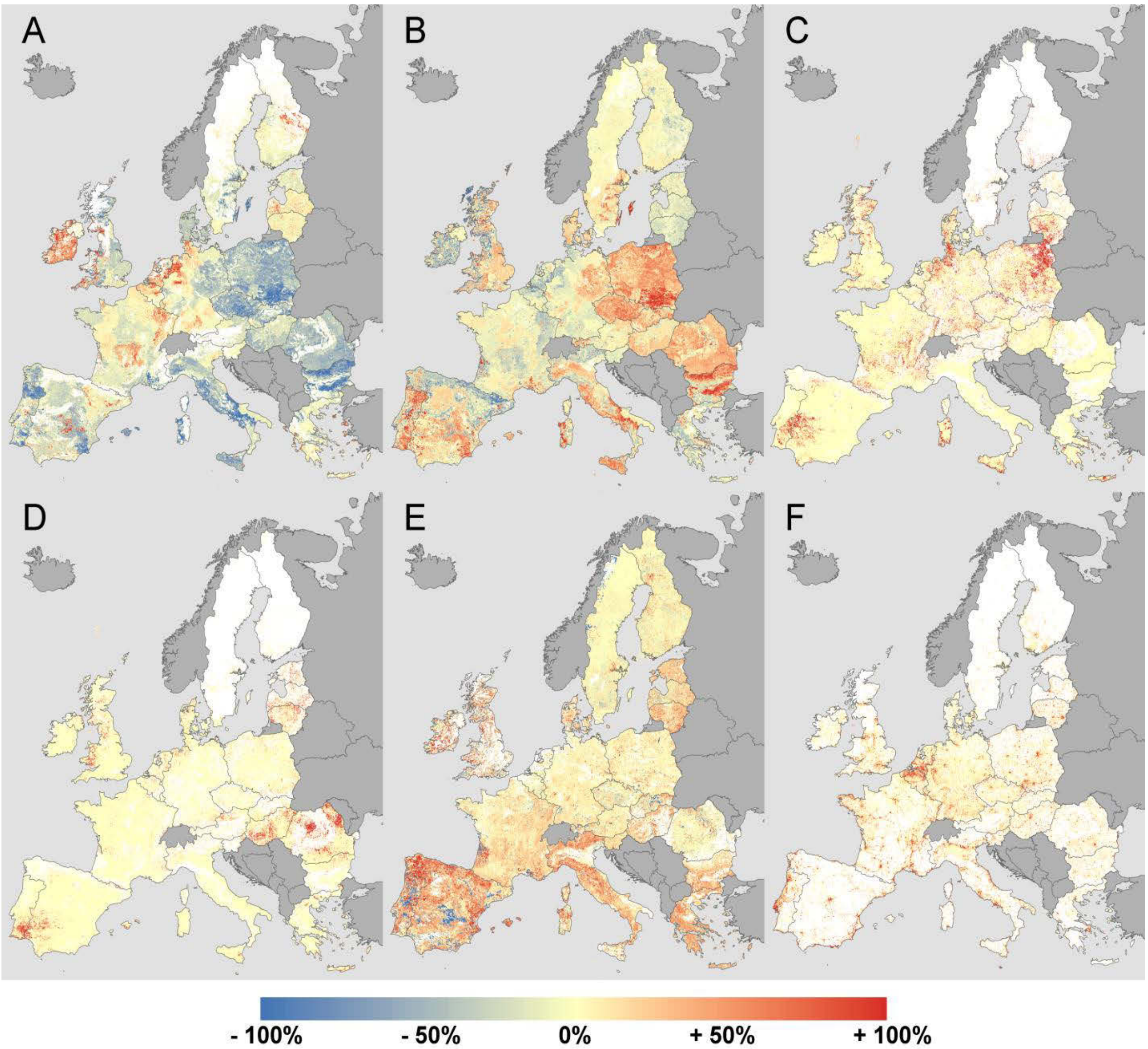

Figure A-1: Spatial patterns of area changes of broad land-use categories in Europe. Panel labels refer to: cropland extent (A), pasture extent (B), farmland abandonment (C), farmland recultivation (D), forestland extent (E), and urban extent (F). Changes refer to the 1990-2006 (A, B, E, F) or 2001-2012 (C, D) periods. Scale refers to relative area changes within a 3x3 km² pixel.

Mediterranean (e.g., Italy, Spain, Figure A-2). Cropland expansion was overall rare and occurred mainly in the Netherlands, northern Germany, central France, and Ireland (Figure A-1A), without major hotspots in Eastern Europe (Figure A-2A). Large areas of Europe were characterised by stable cropland patterns, particularly in southern Scandinavia, Germany, France, and Spain (Figure A-2A).

Pastures were generally stable (Figure A-1B). A few hotspots of pasture expansion between 1990 and 2006 were located in Eastern Europe (e.g., Poland, Bulgaria), Italy, and the Iberian Peninsula, whereas pastures contracted mainly in Ireland, Scotland, the Netherlands, the Pyrenees, and northern Spain (Figure A-2B). Hotspots of farmland abandonment and recultivation mapped from MODIS satellite images were often found in

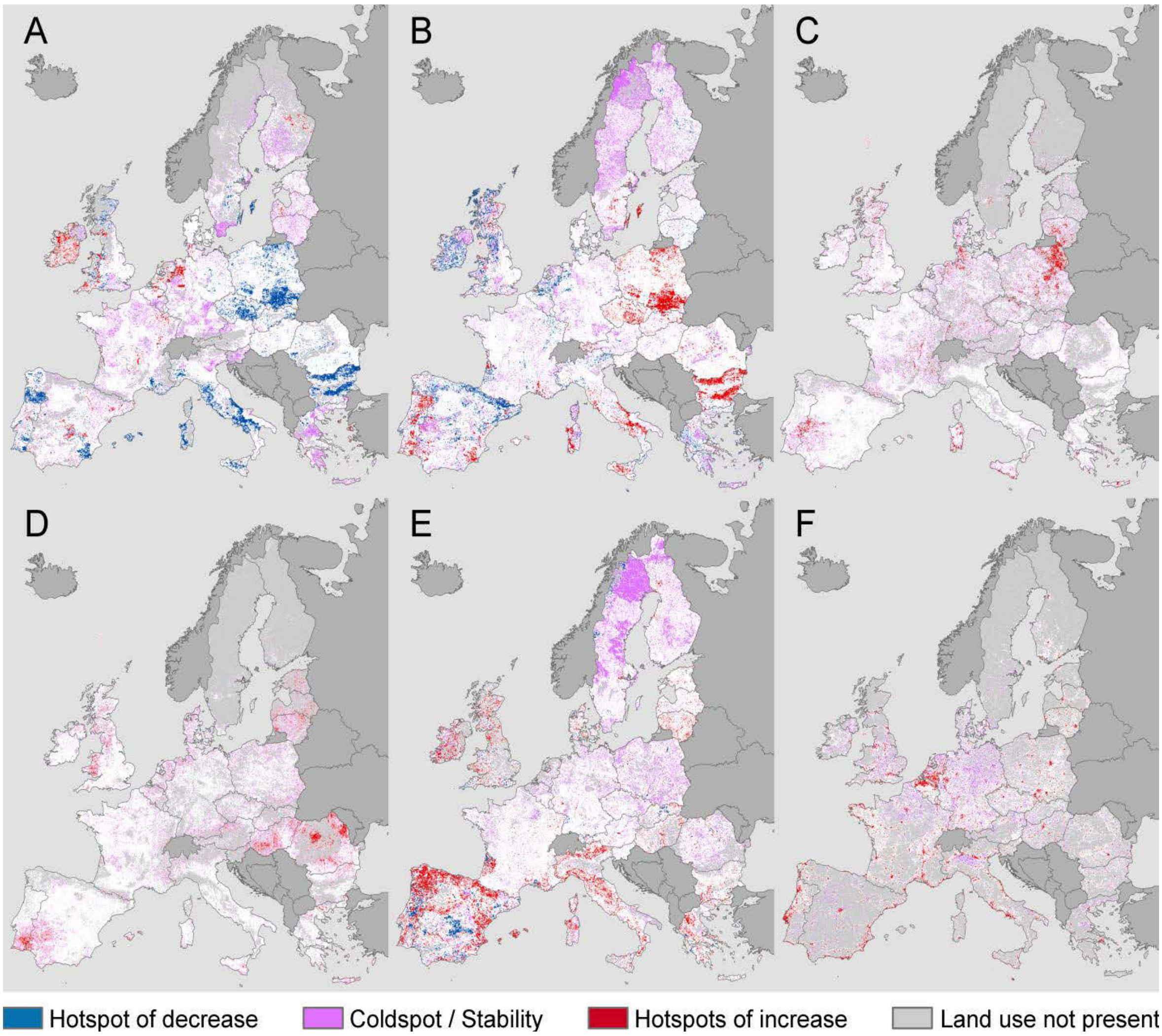

Figure A-2: Hotspots of area changes among broad land-use categories between 1990 and 2006 (2000-2012 for C and D) in Europe. Panel labels refer to: cropland extent (A), pasture extent (B), farmland abandonment (C), farmland recultivation (D), forestland extent (E), and urban extent (F). Hotspots are areas with the 10% largest change values (in positive and negative direction). Coldspots / stability areas entail the 10% smallest change values (both positive and negative) as well as all unchanged areas. White areas refer to areas outside hotspots and coldspots. For hotspots based on 5% thresholds see Figure SI A-1 in the Supplementary Information.

areas where cropland-grassland conversions happened in 1990-2006 (Figure A-1C). Hotspots of abandonment after 2006 were found predominantly in Eastern Europe (e.g., north-eastern Poland, Lithuania) and Scandinavia but some recultivation of formerly abandoned areas was also found in such areas (Figure A-2D).

Most areas in Europe had stable or slightly increasing forestland (Figure A-1E), with hotspots in the Mediterranean (i.e., northern Spain, Italy, Greece), the Baltics, Denmark, United Kingdom and Ireland (Figure A-2E). Forest loss was much less widespread with some hotspots in Spain and Portugal (Figure A-2E). Urban extent increased mainly around major European cities, especially in England, the Netherlands, around Madrid, Lisbon, Helsinki, and Stockholm (Figure A-2F). Urban shrinkage was not a notable land-change trend at the European scale.

3.2 Intensity changes within broad land use categories

Changes in fertiliser use on Europe's cropland varied across Europe during 1990-2006 (Figure A-3). Most hotspots of decline occurred in south-eastern Europe (e.g., Hungary, Romania, Bulgaria), with smaller hotspots of decline in western Germany, western France, and southern England. Fertiliser use increased in eastern Germany, Poland, and the Czech Republic, northern Italy, and central Spain. Many areas characterised by intensified agriculture remained in our most intensive category (e.g., most of Germany, France, Denmark, Figure A-3A). Patterns of changes in cropland yields showed a similar East-West pattern, consistent with changes in input-intensity (Figure A-3B). Stable or increasing

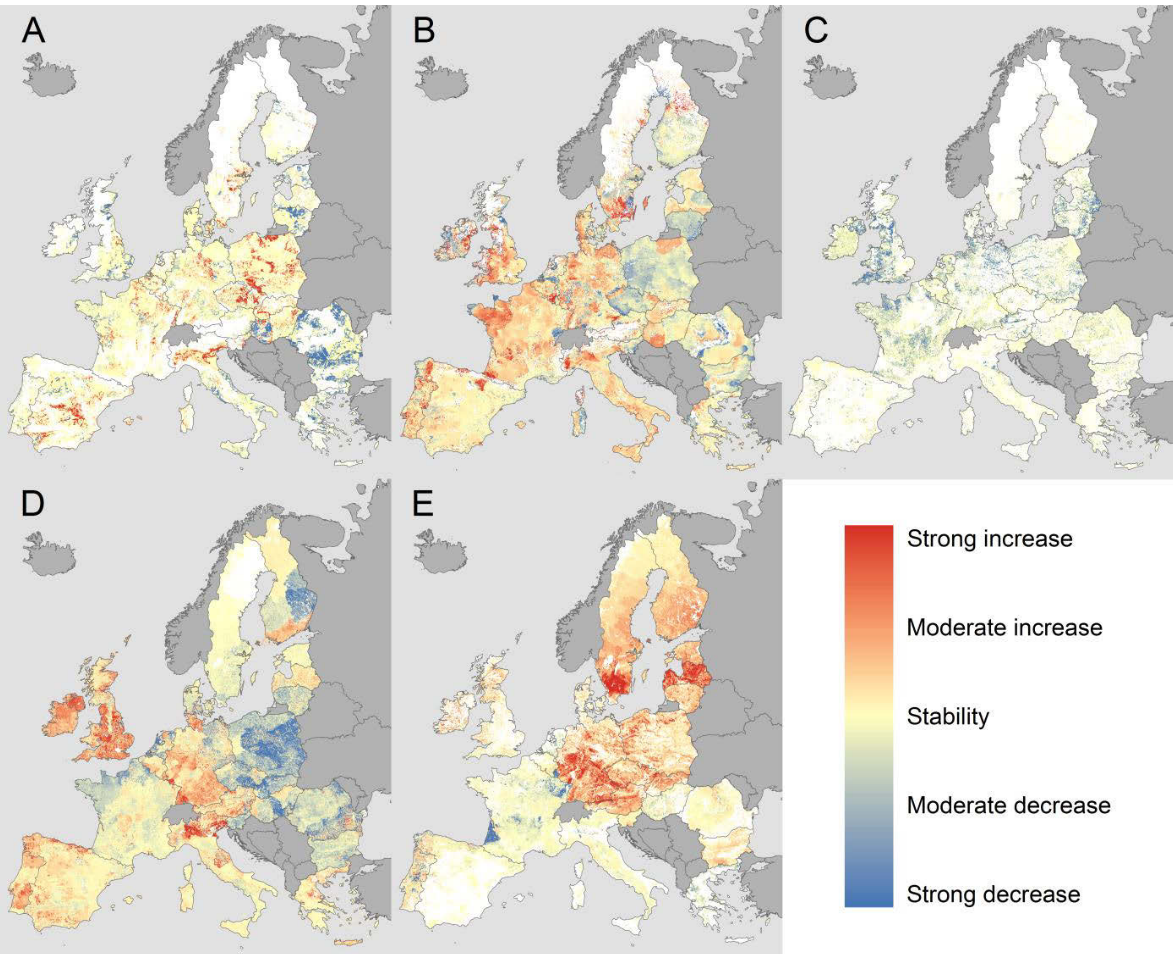

Figure A-3: Spatial patterns of changes in the intensity within broad land-use classes in Europe between 1990 and 2006. Panel labels refer to: cropland fertiliser use [scaled between -120 and +150 kg ha^{-1}] (A), cropland yields [+/-1kg C m^{-2}] (B), pasture livestock density [-90; +25 livestock units] (C), pasture biomass removal [+/-1kg C m^{-2}] (D), and wood removals [-14.2; + 7.6 m^{-3} ha^{-1}] (E).

yields were found throughout much of Western Europe, and yield decreases in many Eastern regions (e.g., Poland, Czech Republic, and Bulgaria, Figure A-4B). Livestock density declined across most of Europe (Figure A-3C), most notably in the UK, northern Germany, the Baltics, and central France (Figure A-4C). Grassland intensity, measured in biomass removal, also showed a clear East-West gradient (Figure A-3D), with strong declines in Eastern Europe (e.g., Poland, Romania, Bulgaria, and Hungary, Figure A-4D).

Regarding forestry, wood harvest volumes remained relatively stable or increased slightly between 1990 and 2006 in most regions (Figure A-3E). Increases in harvesting occurred mainly in southern Sweden, Latvia, in southern and western Germany, Austria, Czech Republic and Poland (Figure A-4E). Decline in forest harvesting occurred mainly in France, Luxembourg and Portugal (Figure A-4E).

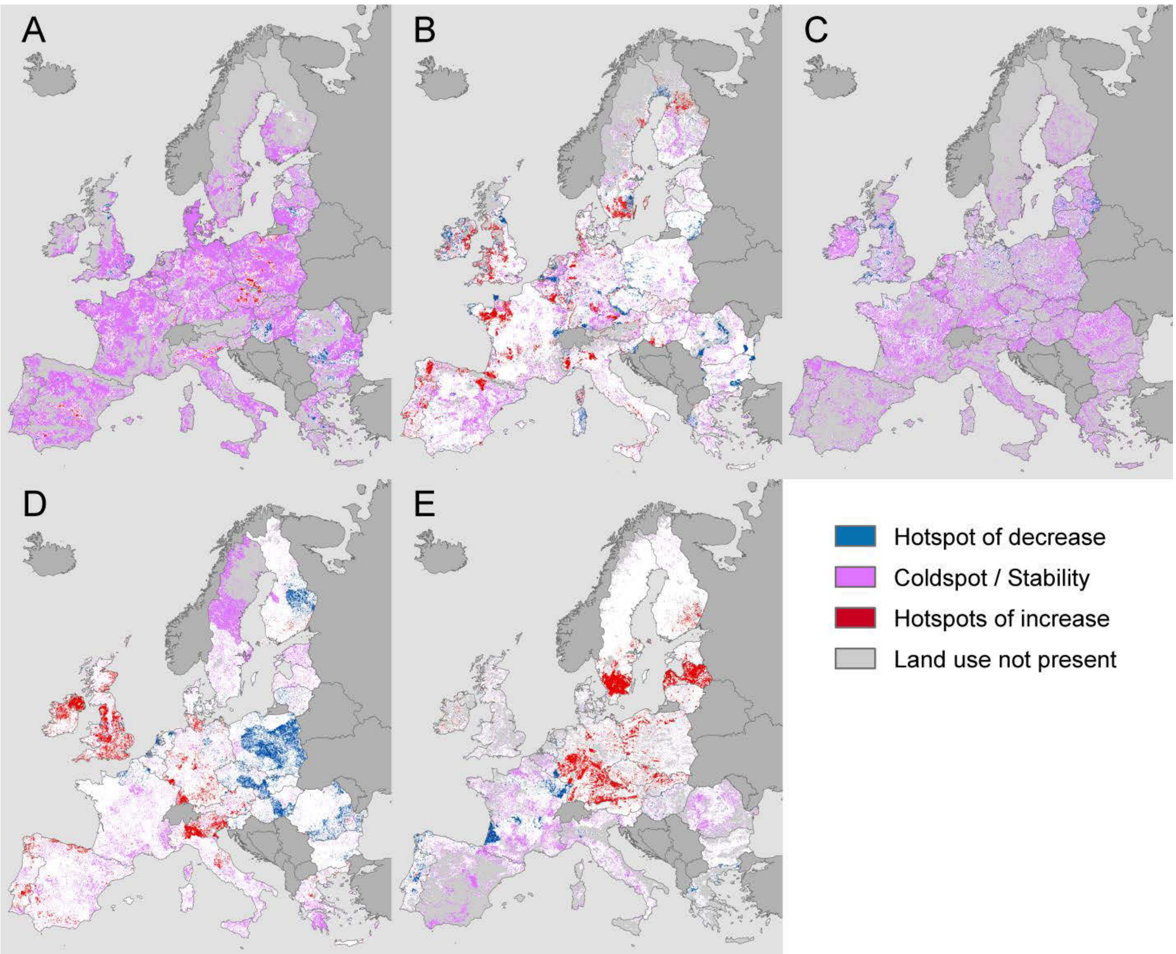

Figure A-4: Hotspots of intensity changes between 1990 and 2006 in Europe. Panel labels refer to: cropland fertiliser use (A), cropland yields (B), pasture livestock density (C), pasture biomass removal (D), and wood removals (E). Hotspots are areas with the 10% largest change values (in positive and negative direction). Coldspots / stability areas entail the 10% smallest change values (both positive and negative) as well as all unchanged areas. White areas are outside hotspots and coldspots. For hotspots based on 5% thresholds see Figure SI A-2 in the Supplementary Information.

3.3 Summarising across hotspots of area and intensity changes

Hotspot areas had surprisingly little overlap (Figure A-5). While the highest number of co-occurring hotspots was seven, only 1.8% of all areas within any hotspots areas were included in four or more hotspots. Seventy percent of all hotspot areas were classified as only one type of hotspot.

Overlaying area and intensity changes (Figure A-6) confirmed the insights from the individual indicators - specifically the strong East-West divide and the relative stability of large areas in Europe in terms of both area and intensity change (grey areas in Figure A-6A-E). However, the overlay also showed interesting patterns of co-occurrence of land-change processes. Generally, few areas were characterised by significant associations of increases in area *and* intensity (black areas in Figure A-6F-J), Notable examples of this pattern include Western Europe regarding cropland (Figure A-6G), or Portugal and England regarding pastures (Figure A-6I). Co-occurrence of area decline and intensification (cyan areas in Figure A-6F-J) was more dominant, for example regarding cropland area and fertiliser use in many Eastern European areas (Figure A-6F) or regarding pastures and biomass yield in Western and Central Europe (Figure A-6I). Area increase co-occurring with disintensification (red colours in Figure A-6F-J) were scattered for cropland while much of Eastern Europe had increasing pasture areas and declining biomass yields (Figure A-6I). In terms of forestry, a clear pattern of declining intensity and increasing forest extent was visible in the Mediterranean and Western Europe, whereas increased

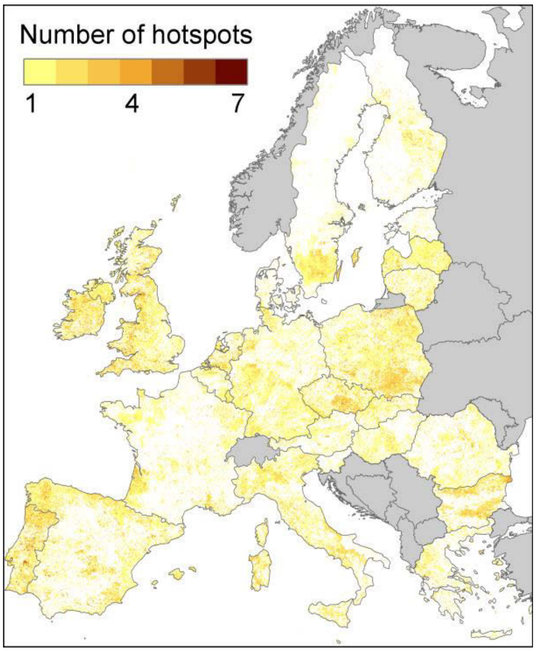

Figure A-5: Number of overlapping hotspots of land use change between 1990 and 2006 (either hotspots of increase or decline in a particular factor) across Europe (highest possible number = 11).

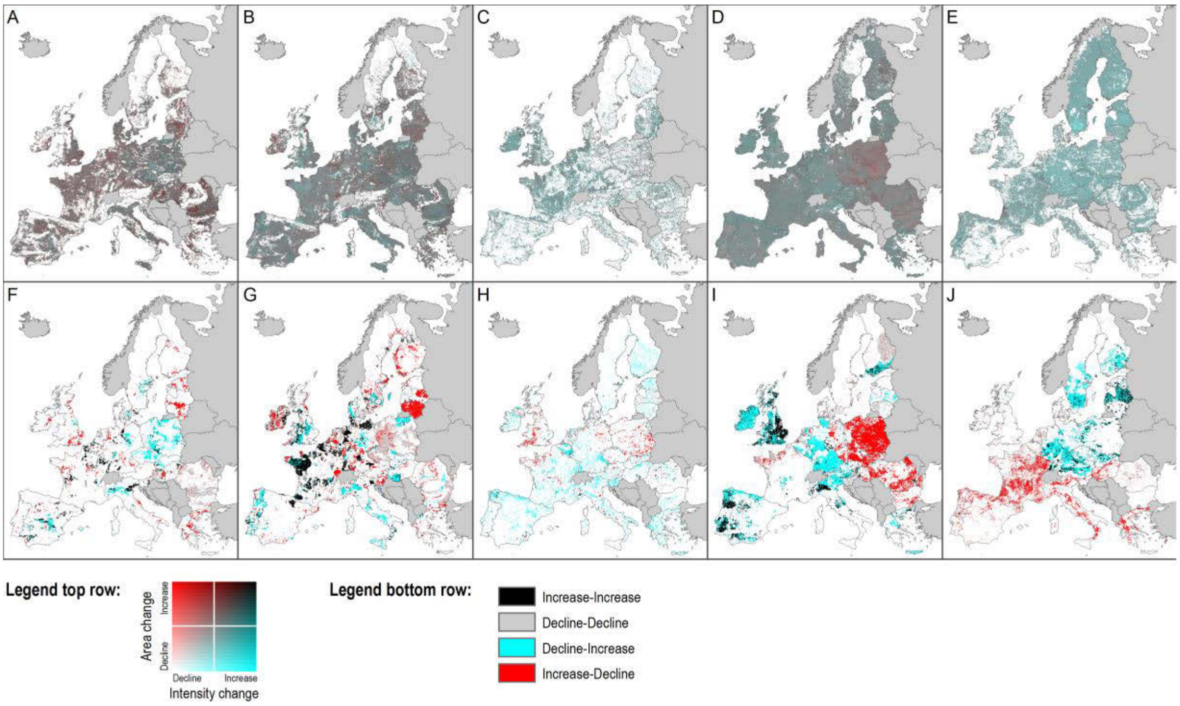

Figure A-6: Area changes vs. land-use intensity changes between 1990 and 2006. Top row: concordance maps of changes in (A) cropland area vs. fertiliser use, (B) cropland area vs. yields, (C) pasture area vs. fertiliser use, (D) pasture area vs. yields, and (E) forest area vs. wood removals. Bottom row: Clusters of significant associations of area and intensity changes (increase/increase, increase/decline, decline/increase, and decline/decline) for changes in (F) cropland area vs. fertiliser use, (G) cropland area vs. yields, (H) pasture area vs. fertiliser use, (I) pasture area vs. yields, and (J) forest area vs. wood removals. Spatial association were significant based on Moran's I ($p<0.05$).

harvests on stable or declining forest area in Central and Northern Europe emerged (Figure A-6J). Overall, Western Europe was characterised as stable or intensifying while Eastern Europe exhibited stable or declining agricultural extent and intensity.

4 Discussion

We analysed spatial patterns in conversions among broad land-use classes as well as changes in management intensity within these classes to reveal the substantial spatial variation in land-change processes in Europe since 1990. The most dominant pattern we found was a clear East-West divide in terms of land change, particularly in terms of agriculture, with stronger declines in cropland area and lower management intensity in Eastern Europe. These patterns likely resulted from the combined effect of the breakdown of socialism, 20th-century land management legacies, and farmers' access to agricultural subsidies in Western Europe. A second common pattern that emerged from our analyses was the diverging trends of stable or intensifying land use in areas highly suitable for farming, and disintensification and abandonment in less suitable areas. This is likely explained by the ongoing structural change towards agri-business and outmigration from rural areas. While we found relatively moderate overall rates of land-use change, many regions in Europe fell into at least one land-change hotspot, and pockets of co-occurring area decline and intensification, as well as co-occurring area increase and disintensification were scattered across most of Europe.

The strong East-West divide during 1990-2006, with fairly constant cropland area but stable or increasing management intensity in the West, and declining cropland area and intensity in the East (Figure A-1, Figure A-3) can be explained by three factors. First, the breakdown of socialism in 1989 triggered a drastic reorganisation of Eastern Europe's agricultural sectors, which resulted in massive ownership changes, declining returns due to price liberalisation and diminishing state-support. Widespread farmland abandonment ensued (Henebry 2009, Schierhorn et al. 2013, Estel et al. 2015) along with a strong decline in capital-intensive farming practices (e.g., less use of pesticides and fertiliser due to increasing prices) (Rozelle and Swinnen 2004). Second, many areas in Eastern Europe were never collectivised and industrialised, and thus did not reach the intensity levels of the West (Palang et al. 2000, Rozelle and Swinnen 2004, Fischer et al. 2012), this is illustrated by the lower management intensity of farming we found for many regions in Eastern Europe (Figure A-3). Agricultural intensification in the 19th and 20th century also began later and progressed slower in Europe's East than in its West, and these legacies prevail to present day (Jepsen et al. 2015). Third, while farmers in Western Europe benefitted in the 1990s from a massive support system under the EU's Common Agricultural Policy (CAP), Eastern Europe's farmers had no access to these subsidies during most of our study period. This changed with the accession of many Eastern European countries to the EU in 2004 and 2007, after which we found hotspots of cropland expansion in 2006-2012 (Figure A-1). The potential importance of CAP subsidies is also highlighted by East Germany, which joined the EU in 1990 via the reunification, and where abandonment was lower and intensity higher than in other post-socialist countries (Niedertscheider et al. 2014).

A second major land change trend in the EU-27 after 1990 was the contraction of cropland area in Western Europe (Figure A-1), mainly in areas with agricultural constraints (e.g., mountain regions, the Mediterranean, Northern Europe, Figure A-2). Many marginal areas in Europe experienced outmigration and a decline in profitability of traditional farming, leading to abandonment (MacDonald et al. 2000, Rutherford et al. 2008, Navarro and

Pereira 2012, Müller et al. 2013, Stellmes et al. 2013). Moreover, CAP changes during our study period resulted in farm support linked to production declining from 87% in 1989 to 27%, in 2009, and the initiation of major set-aside schemes (Moore and Lobell 2015). Marginal croplands were likely the first to be cultivated with low intensity or to be set aside as highlighted in our analysis where widespread cropland to grassland conversions were found in marginal areas (Figure A-1). Finally, increasing displacement of cropland production outside the EU contributed further to Europe's declining cropland area (Kastner et al. 2014).

Cropland contraction was small in regions well-suited for farming in Western and Central Europe, where land-use intensity remained high and stable after 1990. In Eastern Europe, fertile regions such as southern Romania, Hungary, the Czech Republic or some parts of Poland, had much lower abandonment rates and were even hotspots of cropland expansion and increasing intensity (e.g., fertiliser use) after 2006. This suggests an increasing concentration of agriculture, in suitable areas, often occurring next to areas characterised by disintensification and abandonment (Figure A-6). Yield increases in intensifying areas were also moderate, potentially as a result of the decoupling of subsidy payments and commodity outputs, policies to reduce fertiliser use, and climate change (Rounsevell et al. 2012, Moore and Lobell 2015).

Forest area increased across most of Europe. Hotspots of forest increase mainly occurred in regions characterised by cropland and pasture decline (Figure A-1) linked to ongoing urbanisation and rural exodus (Poyatos et al. 2003, Piquer-Rodríguez et al. 2012, Stellmes et al. 2013). Gains in forestland also occurred in regions with afforestation programs (e.g., United Kingdom and Ireland, Zanchi et al. 2007). These trends are likely part of a more long-term recovery from historical deforestation. This recovery happened earlier in Western and Central Europe compared to Eastern and Southern Europe (Rudel et al. 2005, Meyfroidt and Lambin 2011, Kuemmerle et al. 2015). Our results also showed that changes in forestland were spatially not correlated to changes in wood removals, highlighted by the increasing harvests on stable forestland in Northern, Central and Eastern Europe versus stable harvests on increasing forestland in the Mediterranean (Figure A-6). This can be explained by the fact that young forests do not lead to increases in harvests and the Mediterranean forest may be more important for other services than wood production. Some of our hotspots of increasing and decreasing wood removals also coincided with regions where major wind-throws resulted in large salvage harvests.

As a whole, our analyses of land-change hotspots and stability revealed the diversity and complexity of land-change patterns in Europe. While most regions were relatively stable in regard to most indicators we assessed, many regions were also identified as at least one hotspot of change. Interestingly, hotspots of change were often rather scattered, with regions dominated by one land trend sometimes bordering regions where the opposite trend was prevailing (e.g., abandonment alongside recultivation/intensification in Eastern Europe). This further emphasises the need for context-specific, regionalised policy-making to identify regions characterised by similar land-change trajectories and navigate land systems toward desired futures. Another major finding from our study in this context is that different intensity indicators can result in very different intensity patterns of hotspots and coldspots. Most importantly, increasing input intensity (i.e., fertiliser use in our case) was not necessarily related to increasing output intensity (i.e., yields) and vice versa (Figure A-3), highlighting the multidimensional nature of land-management intensity (Erb et al. 2013a).

A number of limitations and factors contributing to uncertainty need mentioning. First, while we gathered, to our knowledge, the most comprehensive spatially detailed land change dataset for Europe, we were unable to include some potentially important agricultural (e.g., mechanisation, pesticide use, labour) or forestry indicators (e.g., harvest regime, tree species selection, fertiliser use, extraction of logging residues and stumps), as well as information on non-productive land uses (e.g., recreation). Second, several of the intensity indicators we used are based on statistical data, which are sometimes of unknown reliability and may underestimate intensity (e.g., due to unregistered wood removal). Third, because land-use statistics are often only available at coarse scale (e.g., NUTS-2/3), translating these data to the grid-level requires disaggregation (Neumann et al. 2009, Temme and Verburg 2011, Verkerk et al. 2015). Disaggregation often relies on ancillary data such as land-cover maps, meaning that that uncertainty in input layers may propagate into derivative maps. Finally, several of our indicators represent snapshots in time, which may be less problematic for area changes, but could affect our intensity measures because temporally and spatially variable phenomena may affect management intensity more strongly (e.g., droughts for yields, salvage logging following storms or insect outbreaks).

Understanding the spatial patterns of land-use conversion and intensity changes, and how these relate to each other, is important for understanding land-change trajectories. Our analyses highlight the diverse spatio-temporal patterns of land-change trends and hotspots in Europe, and the importance of jointly considering land conversions and management intensity changes – across sectors. Moreover, our analyses highlight spatially-explicit land changes (e.g., patterns of cropland expansion and contraction), which are typically hidden in regional or national level statistics that highlight net change only. All of this is crucial for better understanding the outcomes of land change for ecosystem service flows and biodiversity, for assessing the trade-offs among different land uses, and to target land-use and conservation policies.

Acknowledgements

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Supplementary Information

Figure SI A-1: Hotspots of land-use area change where hotspots are defined as the top/bottom 5% of the change distribution.

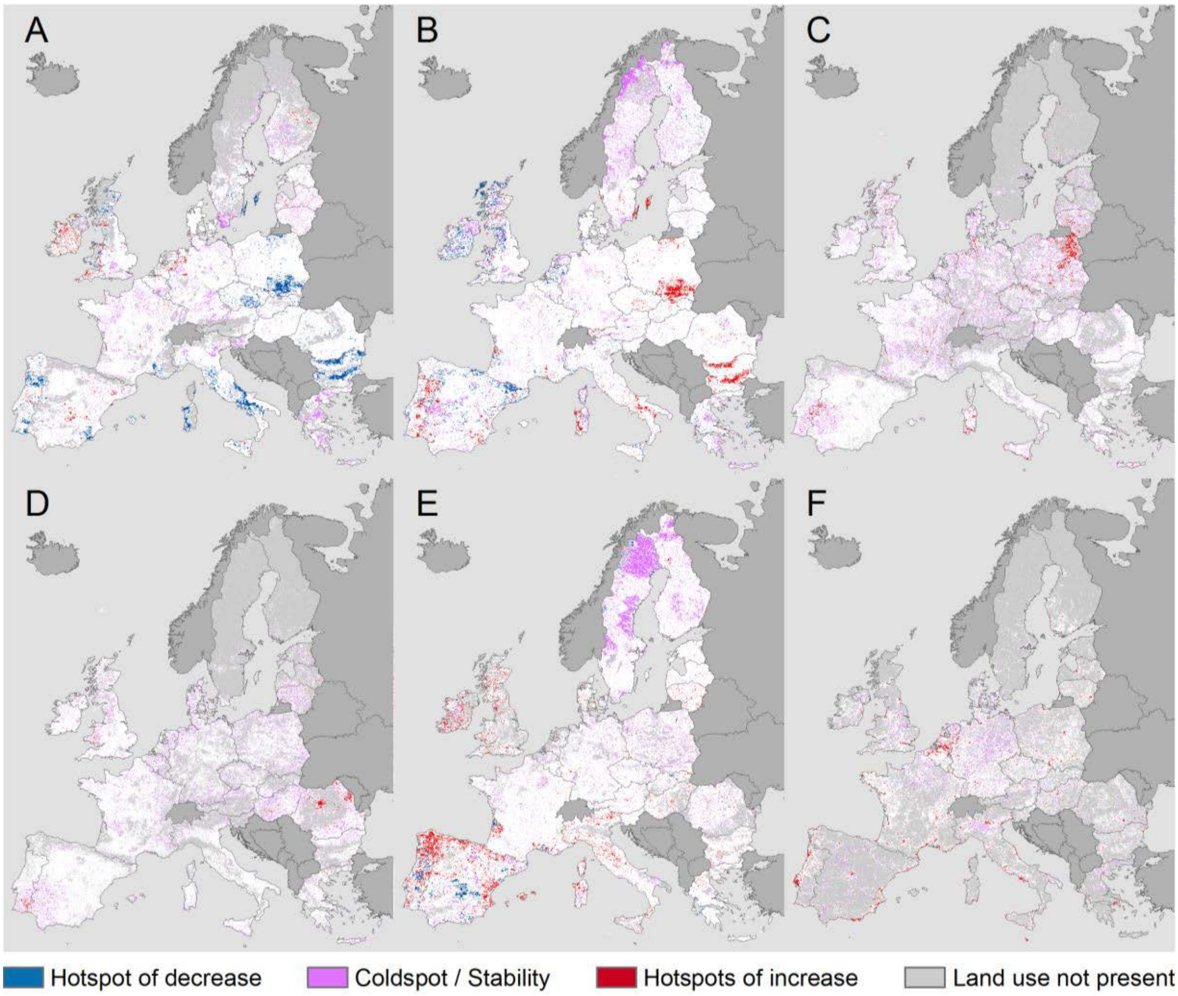
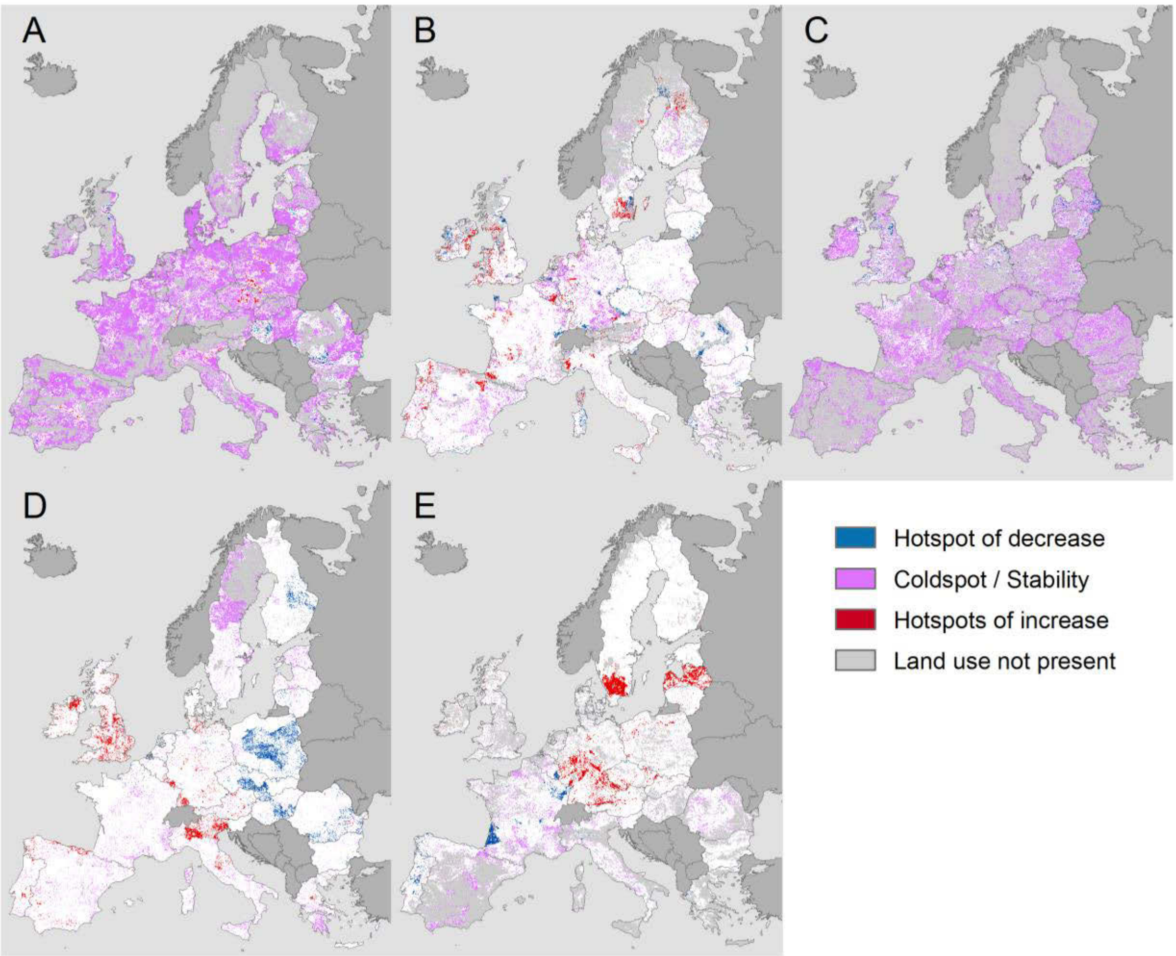


Figure SI A-2: Hotspots of land-use intensity change where hotspots are defined as the top/bottom 5% of the change distribution.



Text SI A-1: Description of land-use change indicators - Data on changes in the extent of broad land-use categories.

We used cropland, permanent crops, and pasture area from the Common Agricultural Policy Regionalised Impact (CAPRI) database (Leip et al. 2008, Britz and Leip 2009) for the years 1990 and 2006 (i.e., corresponding with the CORINE time cuts). Cropland included all arable land including fodder crops, whereas permanents crops included fruit and olive orchards, vineyards, and berries. We regarded the CORINE layers as authoritative for the spatial extent of cropland areas, while using the CAPRI-DynaSpat (Heckelei and Kempen 2011, Leip et al. 2008) for defining the patterns as weights for disaggregating CAPRI statistics to the 3-km grid-level. CAPRI-DynaSpat is, in principle, consistent with CAPRI at NUTS2, but shows small deviations with CORINE. CAPRI-DynaSpat discerns 13 cropland commodity groups (cereals, rice, wine, oilseeds, olives, roots & tubers, fibres, fodder crops, pulses, sugar beet, vegetables & others, and fallow). CAPRI-DynaSpat areas outside of the extent of the CORINE cropland were masked. Cropland areas in CORINE without CAPRI DynaSpat information (very few grid-cells) were allocated to neighbouring grid-cells by applying Euclidian allocation. In some regions (e.g. Mecklenburg-Vorpommern) CAPRI numbers on cropland areas were unreasonably high, likely representing reporting errors. We truncated the CAPRI-DynaSpat cropland amount in these cases using the CORINE cropland area. For a quantitative comparison between CORINE and CAPRI cropland cover please see http://agrienv.jrc.it/publications/pdfs/HNV_Final_Report.pdf, (p29 and p81).

For pasture areas we first allocated the class “meadows & pastures” from CAPRI to the extent of the CORINE pastures class (excluded the class ‘Sparsely vegetated areas’). CAPRI reports significantly larger pasture areas in all NUTS-2 regions than the CORINE pasture class (which is essentially a grassland class). Thus, in a second step, the remaining CAPRI pasture areas were assigned to the CORINE classes ‘heterogeneous agricultural areas’, as well as ‘shrublands and herbaceous vegetation not designated as pastures’. For further details on the allocation procedure for cropland and pastures please see Plutzar et al. (2015).

To map farmland abandonment and recultivation, we used time series of MODIS Normalised Differenced Vegetation Index (NDVI) for the time period 2000 to 2012 at a spatial resolution of 231m (Estel et al. 2015). We applied a multi-step pre-processing chain to reduce effects arising from clouds, water, ice, and soil background, and thus to construct a consistent NDVI time-series. We also normalised the NDVI time series to make them more comparable across the broad environmental gradients prevailing in Europe.

Second, for the years 2001 to 2012, we classified each grid cell as either managed (i.e., active, ploughed, mowed or heavily grazed) or fallow (i.e. unmanaged) and finally applied the CORINE agricultural mask (i.e., all classes with non-permanent cropland and pastures). To do so, we used a RandomForests classifier (Cutler et al. 2007, Waske et al. 2012), with training data sampled across Europe using a random-stratified setup. Independent validation data came from the Land Use/Cover Area Frame Statistical Survey (LUCAS, www.lucas-europa.info), field campaigns, and higher-resolution satellite images (e.g., GoogleEarth imagery). LUCAS provides ground information on land cover and land management (Delincé 2001, Gallego and Delincé 2010, van der Zanden et al. 2013), including fallow, abandoned and active farmland. For LUCAS 2009 and 2012, for instance, around 500,000 points were surveyed and photo-documented by field surveyors in 23 (2009) and 27 (2012) EU countries (Eurostat 2014).

Training and validation data were crosschecked to ensure field labels were correct, as class labels may have changed after a plot was surveyed on the ground (e.g., ploughing of a fallow field after a site was visited) using the temporal profiles of the MODIS NDVI time series and high-resolution imagery in GoogleEarth. The resulting annual active/fallow maps had an average overall accuracy of 89.8% (standard deviation of 1.1%). Using the active/fallow time series, we defined (i) agricultural abandonment (max. 2x fallow in 2001-2006 and max. 1x active in 2007-2012) and (ii) recultivation (max. 1x active in 2001-2006 and max. 2x fallow in 2007-2012). For details see Estel et al. (2015). We then summarised abandonment, and recultivation and at the 3-km grid level.

Assessing changes in forest land from satellite-based land cover maps such as CORINE is challenging, because forest cover changes can reflect permanent gains or losses in forest area, but also temporary cover losses due to natural disturbance (e.g., storms or fire) or management (e.g., harvest), which do not reflect land use change. To derive forest land maps, we disaggregated and harmonised regional level forest area statistics (see Levers et al. 2014 for details) for the years 1990 and 2005 to the 3-km grid using CORINE forest area as weights (Plutzar et al. 2015).

To calculate the extent of urban area change, we relied on the 1990 and 2006 CORINE maps and calculated percent urban land cover within 1 km^2 cells based on the 11 urban or built-up classes, following the protocol by Feranec et al. (2012). Further details on the allocation procedure for forestland and urban area are provided in Plutzar et al. (2015).

Text SI A-2: Description of land-use change indicators - Data on changes in the management intensity within broad land use categories.

To measure cropland inputs, we relied on a recently developed 1-km dataset of fertiliser application rates (Overmars et al. 2014, Temme and Verburg 2011). This dataset was generated using statistics on fertiliser use data at the NUTS-2 level from the CAPRI database, which contains both manure and chemical fertiliser input for all major crops for 1990 – 2007 from the Farm Structure Survey (see Britz and Witzke 2014 for details). To summarise the fertiliser data across crop types, cropland area at the NUTS-2 level was stratified into three fertiliser input classes: low (<50 kg/ha), medium (50-150 kg/ha) and high (>150 kg/ha) (Overmars et al. 2014). Next, multinomial regression models were fitted to create probability maps for each class and for each country. As response variable, ~150,000 cropland points from LUCAS were used, to which crop-specific nitrogen application rates had been assigned. As predictors, a set of environmental (i.e., soil, topography, climate) and socio-economic (i.e., population density and accessibility) factors at a resolution of 1 x 1 km^2 was used (Overmars et al. 2014, Temme and Verburg 2011). For countries without LUCAS coverage, regressions from neighbouring countries were applied. Using the resulting probability maps, a hierarchical procedure was then used to allocate the NUTS-2 level areas of the three fertiliser application classes to the grid level (Overmars et al. 2014). For the purpose of this manuscript, we aggregated data to the 3 x 3 km^2 for 1990 and 2006 by calculating an area-weighted mean, using the values 50, 150, and 250 kg/ha as class values.

In terms of cropland outputs, we used yields for the 13 most prevalent crops types defined by CAPRI-DynaSpat in the EU (i.e., cereals, oilseeds, pulses, roots & tubers, sugar beet, olives, flax & hemp, wine & grapes, fruits, rice and vegetables) from the CAPRI database at the NUTS-2 level for 1990 and 2006. Yields were expressed as the amount of biomass harvested per crop. To disaggregate yields to the 3-km grid, we derived crop suitability maps using environmental niche modelling, in our case based on a maximum entropy algorithm (Phillips et al. 2006, You and Wood 2006). Niche models require data on the occurrence of a particular species (in our case a specific crop), which we took from the LUCAS database. Maxent then describes the niche of a crop based on environmental factors by contrasting the distribution of values of an environmental factor at the occurrence locations with the overall distribution of this factor. As environmental factors (i.e., predictors), we used bioclimatic, soil, and topographic variables. The resulting crop suitability maps were combined with the cropland area maps described above by calculating the product of cropland share and suitability. These layers then served as weights for the disaggregation of harvest yields (see Plutzar et al. (2015) for details), resulting in a map of the amount of biomass harvested on cropland area per grid-cell [tC km^{-2} yr^{-1}].

Regarding grazing systems, we used one input and one output metric. Regarding inputs, we derived grazing intensity on pastures by downscaling NUTS-2 level livestock numbers to the 1-km grid level following Neumann et al. (2009). The NUTS-2 level statistics do not distinguish between grazing and stall feeding, and we assumed that all dairy cattle, beef cattle, heifers, sheep, and goats were dominantly grazing. We converted all livestock numbers to equivalent livestock units using region-dependent conversion factors. We then used a grazing potential map, using grassland productivity, terrain, and accessibility as main determinants (see Neumann et al. 2009), to spatially allocate these livestock units. Areas with very low grazing potential were not allocated any livestock. Based on the resulting livestock densities, four grazing intensity categories were distinguished (1: <25 LSU/km^2; 2: 25-50 LSU/km^2; 3: 50-100 LSU/km^2; 4: >100 LSU/km^2). We then calculated an area-weighted mean at the 3x3 km^2 grid using class means (100 LSU/km^2 for the fourth class).

In terms of output metrics, we used biomass yields and calculated biomass removed from pastures (in tC km^{-2} yr^{-1}) from CAPRI at the NUTS-2 level and disaggregated these to the 3-km grid level, using a combination of actual NPP and slope as weights, assuming a linear decrease of pasture suitability between 6% and 24% slope (Neumann et al. 2009). Actual NPP was taken from Plutzar et al. (2015), slope was calculated on the basis of the SRTM30 digital elevation model (www.cgiar-csi.org/data/srtm-90m-digital-elevation-database-v4-1). No metrics regarding changes in the input intensity of grazing systems were available to use.

To assess forestry intensity, we compiled and harmonised annual wood removal maps based on regional harvest statistics from 2000 to 2005 at the level of administrative units (Levers et al. 2014). Within the current study, we disaggregated these regional harvesting statistics using the above mentioned forest cover map (cf. Text SI A-1), which was combined with a pixel-level harvest likelihood map to produce wood removal maps at the target resolution of 3x3km. This likelihood map was derived using linear regression modelling to link harvesting statistics with productivity, tree species composition, and terrain ruggedness as the most important location factors (see Verkerk et al. (2015) for details on the harvest likelihood maps and disaggregation approach). To extend the time period covered, we disaggregated national-level harvesting data from Forest Europe et al. (2011) for 1990, assuming constant harvesting ratios among regions within a country, which is supported by the very stable harvesting patterns found by Levers et al. (2014). We assigned wood removal volumes only to grid cells that were forests already in 1990. New forests either established or deforested after 1990 were assumed not to supply wood in 2005, due to long production cycles in forestry.

Publikationen

PEER-REVIEWED JOURNAL ARTICLES

Published or accepted manuscripts

[13] **Levers, C.**, Müller, D., Erb, K., Haberl, H., Jepsen, M.R., Metzger, M.J., Meyfroidt, P., Plieninger, T., Plutzar, C., Stürck, J., Verburg, P.H., Verkerk, P.J. & Kuemmerle, T. (accepted). Archetypical patterns and trajectories of land systems in Europe. Regional Environmental Change, online first.

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[3] Kuemmerle, T., Stürck, J., **Levers, C.**, Müller, D., Erb, K., Gingrich, S., Jepsen, M.R., Kastner, T., Verkerk, P.J. & Verburg, P.H. (2014). Interpretation of scenario results in terms of described and mapped land change trajectories and archetypes. VOLANTE deliverable No. 11.2.

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[11] Nützmann, G., **Levers, C.** & Lewandowski, J. (2014). Simulating transient aquifer-stream exchange at the lowland River Spree (Germany) with a coupled groundwater flow and heat transport model. Computational Methods in Water Resources, Stuttgart, Germany. June 2014. *Poster presentation*.

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Eidesstattliche Erklärung

Hiermit erkläre ich, die vorliegende Dissertation selbstständig und ohne Verwendung unerlaubter Hilfe angefertigt zu haben. Die aus fremden Quellen direkt oder indirekt übernommenen Inhalte sind als solche kenntlich gemacht. Die Dissertation wird erstmalig und nur an der Humboldt-Universität zu Berlin eingereicht. Weiterhin erkläre ich, nicht bereits einen Doktortitel im Fach Geographie zu besitzen. Die dem Verfahren zu Grunde liegende Promotionsordnung ist mir bekannt.

Christian Levers

Berlin, den 04.01.2016